Production Gaps Among Disabled Farmers Is Associated with Limited Technology

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Abstract

In sub-Saharan Africa, agriculture is vital; however, the systematic exclusion of persons with disabilities from farming hinders sustainable development and social equity. While several studies have analyzed productivity differentials across various dimensions of social exclusion, empirical evidence on technology adoption, farming efficiency, and productivity gaps among farmers with disabilities remains limited. This study addresses this gap by evaluating disparities in crop production between farmers with and without disabilities in Ghana, with particular focus on differences in technology access and production efficiency. Utilizing meta-stochastic frontier analysis coupled with statistical matching techniques on nationally representative farm-level data from the 2012/13 and 2016/17 agricultural seasons, we find negligible differences in technical efficiency between the two groups (less than 0.5%). However, the productive capacity of the technology sets employed by farmers with disabilities is approximately 11 percentage points lower than that of their counterparts without disability, resulting in a 9.5 percentage points shortfall in crop production. This production shortfall is primarily driven by reduced per-hectare use of critical inputs such as planting materials, labor, fertilizer, and agro-chemicals. These findings highlight a significant disability-induced technology access gap which reflects broader structural inequalities. Addressing these disparities is essential for promoting equitable agricultural development while harnessing the full potential of all farmers in Ghana.

Keywords: disability parity; agricultural technology; technical efficiency; Ghana; production gap

JEL Classification: J14, Q12, O13, O33, I38

1. Introduction

Globally, an estimated 1.3 billion people, or about 16% of the world's population live with significant disabilities (WHO 2023). A significant majority, around 80% of these individuals reside in low- and lower-middle-income countries (World Bank 2024). According to the World Health Organization (WHO) (2011), disability is an "umbrella term for impairments, activity limitations and participation restrictions, referring to the negative aspects of the interaction between an individual (with a health condition) and that individual's contextual factors (environmental and personal factors)". Disabilities can vary widely; they may be visible or invisible and may encompass physical, intellectual, cognitive, or sensory impairments (United Nations, 2006). Extensive research reveals that these challenges intensify issues for persons with disabilities (PWDs) and their households, leading to pronounced disparities in food insecurity (Samuel et al. 2023; Opoku et al. 2019), pervasive poverty (Mont and Nguyen 2018; Palmer, Williams and McPake 2019; Gaiha, Mathur and Kulkarni 2022; Asuman, Ackah and Agyire-Tettey 2021; Trani et al. 2015), restricted access to the labor market (Mitra and Sambamoorthi 2008), inadequate housing (Saugeres 2011; O'Donovan and Whittle 2024), and limited healthcare services (Mishra and Narayan 2024; Rana et al. 2024). Recognizing the urgent need to bridge these gaps, the United Nations calls on countries around the world to bolster economic opportunities for all, in line with its ambitious objectives to eradicate poverty and hunger while leaving no one behind as integral components of the Sustainable Development Goals (SDGs) (United Nations 2018). Achieving these objectives, however, depends significantly on evidence-based research to pinpoint and mitigate disparities across diverse economic and social demographics. In this study we treat disability as a household-level attribute, capturing the status of the farmer, immediate relatives, and other members.

In sub-Saharan Africa (SSA), a region where agriculture is the cornerstone of the economy, PWDs are often excluded from farming opportunities (FAO, IFAD, and WFP 2013)—which is a critical issue given agriculture's role in employment, economic growth, and food security. Ensuring equitable access of PWDs to agricultural opportunities is essential for fostering sustainable development and social justice. Yet, the relationship between disability and agricultural productivity, especially in terms of technology adoption and its optimal use, generally remains underexplored. This neglect not only sidelines a significant segment of the PWD community but also fails to recognize their potential to significantly contribute to the agricultural sector and, by extension, the wider economy. While a substantial body of research has gauged productivity differentials across multiple domains of social exclusion, such as ethnicity (Njuki, Lachaud, Bravo-Ureta, and Key 2025), age (Asravor et al. 2024), and gender (Adaku et al. 2023; Owusu, Donkor, and Owusu-Sekyere 2018), empirical evidence remains sparse regarding the extent to which disability shapes differences in technology adoption, production efficiency, and agricultural productivity. This study seeks to bridge this empirical gap and, in doing so, makes a timely and valuable contribution to the literature on agricultural economics, and more broadly, to the field of development economics.

Ghana provides a backdrop for exploring the relationship between disability and agricultural productivity given (i) the country's ongoing efforts to mainstream disability into agricultural and social protection policies (MoFA 2015, 2025; Abdul Karimu et al. 2018) and (ii) the presence of national schemes—such as the Disability Fund and the Livelihood Empowerment Against Poverty (LEAP)—that provide farm inputs or cash support to farmers with disabilities (Abdul Karimu et al. 2018; Opoku et al. 2018). While these initiatives may likely influence the technological endowment and efficiency performance of PWDs, empirical studies scarcely examine how disability status shapes farm-level outcomes. Moreover, despite the practical constraints that disability places on technology access and use within farm households, there remains little empirical understanding of how these conditions shape adoption behavior and input use in agricultural settings. In Ghana, PWDs remain one of the most under-utilized groups in the agricultural sector (MoFA, 2015). As such, understanding how disability influences technology access and farm performance is critical for designing policies that support greater inclusion and address persistent productivity gaps in rural livelihoods. As a middle-income nation that has witnessed substantial GDP growth, Ghana's economy is nonetheless characterized by a significant proportion of its population—between 7-10%—living with disabilities (Agyei-Okyere et al. 2019). Many of these individuals are older, females, and reside in rural areas, where agriculture forms the economic bedrock (Rowland et al. 2014). Despite this demographic's potential to contribute meaningfully to agricultural production, PWDs in Ghana face systemic challenges, including discrimination, unemployment, and broader societal hardships (Opoku et al. 2019; Agyei-Okyere et al. 2019; Kuyini, Alhassan and Mahama 2011; Oteng and Gamette 2024). The role of agriculture as a viable pathway for generating sustainable economic opportunities for PWDs has been underexplored, particularly given the sector's labor-intensive nature and the unique challenges and contributions of PWDs. Historically, PWDs have been marginalized and faced discrimination across various societal dimensions (Agyei-Okyere et al. 2019). This systemic overlook raises a critical yet largely unexplored question: Does this societal backdrop contribute to a discernible disparity in technology adoption and production efficiency, and by extension, agricultural productivity growth for PWDs in Ghana? This question underscores the necessity of examining the agricultural sector not only as a source of livelihood but also as a potential platform for fostering inclusivity and economic empowerment for PWDs.

Our research delves into the nuances of disability parity within Ghana's agricultural sector, with a focus on: (1) assessing the degree of disparity in technology level and technical efficiency of crop production among farmers, considering the disability status of the farmer, their immediate family, or household members; and (2) examining the variations in this disparity across different demographic and agricultural contexts, including gender, age, education level, crop type, and geographical location. To conduct our analysis, we employ a meta-stochastic frontier framework with a specific focus on disability. This approach is applied to data gathered from two cross-sectional population-based surveys conducted in Ghana, encapsulating 19,862 farmers in 2012/13 and 2016/17 across all commercially cultivated crops among others. This dataset, which is nationally representative, offers a rare opportunity to empirically examine how agricultural production factors (such as elasticities, returns to scale [RTS], and technological gaps) and technical efficiency vary with disability. To minimize self-selection bias in technology adoption linked to disability and to reduce model dependency, we utilized statistical matching techniques in creating comparable pairs of farmers with and without disabilities. This strategy allows us to associate any observed disparities in crop production technology and technical efficiency to the disability status of the farmers. By leveraging this approach, our study aims to provide a comprehensive understanding of the possible disability-induced technology and efficiency gaps in Ghana's agricultural landscape, highlighting the specific challenges and opportunities for farmers with disability.

The analysis reveals that farmers with disability have an average technological access index of 0.82 compared to 0.93 for their peers without disability, culminating into an average disability-induced technology gap of 11[1] percentage points in crop production in Ghana. Evaluating the

[1] *Difference in mean TGR between farmers with disabilities and those without disabilities multiplied by 100.*

managerial capacity of farmers in each group relative to their respective frontiers reveals an average score of 0.78, suggesting that farmers with and without disabilities achieve, on average, 78% of their attainable frontier outputs. However, against a common benchmark, which is the meta-frontier, we find that farmers with and without disabilities operate at 63 and 72.5% of the industrial frontier, reflecting a 9.5 percentage points gap against PWDs due to structural differences in production technology. The disability gap in technology access is likely due to obstacles faced by PWDs in accessing farm intensive margin inputs. Access to agricultural inputs for PWDs is significantly limited by financial barriers, with studies indicating that PWDs face exclusion from microcredit schemes (Beisland and Mersland 2012b, 2012a; Peprah et al. 2023) and reduced likelihood of accessing support from formal financial institutions (Beisland and Mersland 2012b; Peprah et al. 2023).

While our core findings indicate that the overall shortfall in crop production associated with disability is robust, the source of this shortfall — whether due to technological endowment (TGR) or technical efficiency (TE) — depends on whose disability we focus on. Specifically, the greater TE scores observed in cases where the "child (adopted or biological) of the farmer only" and "spouse or child of the farmer only" experience disability is offset by larger gaps in TGR. For the disability of other household members, both TE and TGR contribute to the shortfall, with TE being more prominent. This suggests that whilst interventions targeted at addressing both technological access and technical efficiency shortfalls are essential, such interventions should consider the specific member of the household who suffers from disability and their relation to the farmer.

Our research enriches the existing body of literature in multiple significant ways. Notably, while previous studies on production shortfalls in Ghana have predominantly concentrated on factors such as geographical location (Tsiboe, Asravor and Osei 2019; Tsiboe 2021; Tsiboe et al. 2022), age of farm operator (Asravor et al. 2024), and gender (Adaku, Tsiboe and Clottey 2023), we consider a very critical developmental issue of disability in agricultural production. To our knowledge, evidence is not only sparse on this germane developmental issue on the global scale but also notably absent in the discourse on disability parity within the context of SSA. Further, continental studies have only demonstrated gaps in access to land by PWDs with sparse empirical evidence on intensive margin input access and use (Tom 2024). Our study expands the scope to include access to intensive margin inputs like planting materials, labor, fertilizer, and agro-chemicals. By delving into this underexplored area, our study not only fills a crucial gap in literature but also broadens the understanding of the complex interplays affecting agricultural productivity, thereby contributing to a more inclusive approach in agricultural research and policy formulation.

The remainder of this paper is structured as follows. Section 2 outlines the data sources, construction, and presents descriptive statistics to contextualize the study. This section also examines the current state of farmers with disability in Ghana, providing a foundational understanding of their challenges and opportunities. Section 3 details the methods employed and discusses the identification strategy for the empirical investigation. In section 4, we delve into the results and their implications, offering a discussion that situates our findings within the broader literature. Finally, the paper concludes in section 5 with a summary of our findings, their significance for policy and practice, weaknesses, and suggestions for future research.

2. Data

2.1 Data sources and construction

This study utilizes farm-level data from the two most recent Ghana Living Standards Surveys (GLSS), conducted in 2012/13 (GLSS6) and 2016/17 (GLSS7). These surveys, designed as repeated cross-sectional studies, implement a two-stage sampling methodology, initially selecting enumeration areas, followed by households. The data from GLSS have been consolidated into a comprehensive farmer-level dataset (Tsiboe 2020), facilitating in-depth analysis of agricultural productivity across various value chains in Ghana (Tsiboe et al. 2019; Tsiboe, Egyir and Anaman 2021; Tsiboe, Aseete and Djokoto 2021; Tsiboe 2021; Tsiboe et al. 2022). Our analysis is restricted to crop farmers from these surveys, specifically those whose yields (in kg/ha) fall between the 2.5th and 97.5th percentiles, segmented by survey iteration and crop. The final sample comprised 19,862 farm operators, cultivating at least one of the following crops: banana, beans, cashew, cassava, citrus fruits, cocoa, coconut, cocoyam, cotton, kenaf, maize, millet, palm, peanuts, plantain, potato, rice, sorghum, yam, sugarcane, tomato, pepper, okra, onion, eggplant, and various other crops.

The consolidated dataset (Tsiboe 2020) provides harmonized farm-level outcomes across GLSS6 and GLSS7 but does not directly contain disability indicators. To construct these, we returned to the foundational GLSS datasets, which preserve the original enumeration area, household, and member identification variables as well as detailed disability-related questions. Using these identifiers, we integrated disability information into the consolidated dataset.

An individual is classified as having a disability if they reported: (i) being unable to attend school, work, or seek employment due to disability or illness; (ii) having a serious disability that limited participation in daily life activities such as mobility, work, or social life; or (iii) experiencing discrimination or exclusion from community-level activities specifically because of disability. In addition, respondents could indicate the type of disability—sight, hearing, speech, physical, intellectual, emotional, or other—with multiple responses permitted. For clarity, Table S1 in the online appendix details the questions used, the preferred responses (in braces), and the number of choices allowed.

We explicitly excluded short-term illness and injury measures recorded in Section 3a of the GLSS (e.g., "During the last 2 weeks, has [NAME] suffered from an illness or injury?") from our disability definition, as these capture temporary conditions rather than long-term limitations. Accordingly, our operational definition reflects both congenital and acquired disabilities but does not disentangle between them, in line with the survey design. Based on this formulation, 9.43% of the sample had a disability as defined above. This included disabilities reported by the farmer (9.42%), their immediate family (4.79%), or other household members (5.48%). These categories are not mutually exclusive, and therefore their combined percentages exceed 8.86%. Unless otherwise specified, the term 'farmer(s) with disability' throughout this paper refers to disability status as reported by the farmer, their immediate family members, or other members of their household.

2.2 Descriptive statistics

The summary statistics reveal notable differences between farm households with and without disability in Ghana. About one-quarter of respondents are female, with an average age of 47 years, four years of education, and household sizes averaging 5.4 members. The mean total crop value is GH₵ 1,281, with maize having the highest value (GH₵ 2,531) and okra the lowest (GH₵ 350). Farmers cultivate an average of 1.83 hectares and show moderate crop diversification (0.46). Access to mechanization (5%), irrigation (2%), and credit (12%) remains limited. Farmers with disabilities are generally older, less educated, and more dependent on hired labor, yet they exhibit greater crop diversification and slightly higher use of mechanization than those without disability. Despite these differences, crop choices and overall production levels do not differ significantly by disability status, suggesting that productivity disparities may stem from other observable and unobservable factors explored in subsequent analyses.

2.3 The state of farmers with disability in Ghana

The International Labor Organization (ILO) reports that nearly 80% of PWDs are of working age, underscoring the relevance of disability to labor force participation, including agriculture (ILO 2019). Globally, 70% of PWDs are economically inactive, compared to 40% of those without disabilities (ILO 2022). This gap reflects widespread exclusion of PWDs from employment, including farming. In SSA, disability prevalence is high (e.g., an estimated 12% of the youth in SSA have a disability) (Bannink Mbazzi et al. 2024), yet many rural PWDs remain marginalized in agriculture. Disability prevalence increases sharply with age, and because rural populations are ageing, older farmers are more likely to experience functional limitations than their younger counterparts (WHO 2011; CDC 2022). Data from Kenya show that among smallholders, older participants with disabilities were significantly more likely to exit the labor force compared to younger farmers (Bechange et al. 2024).

Gender further shapes the distribution and impacts of disability. Women tend to report slightly higher disability prevalence than men, particularly in older age groups, and live longer with disabling conditions. In agriculture, these disadvantages are compounded by lower access to land, inputs, and extension services, leaving women with disabilities at heightened risk of exclusion (UN Women 2019).

Although comprehensive global data is lacking, national surveys provide insights into disability in agriculture. In the United States, 12.9% of the farm population live with a disability, with 19.2% of farm operators and 9.0% of farmworkers affected (Jenkins et al. 2012). A recent survey of thousands of Kenyan smallholder farmers found a disability prevalence of 17.2% (20.3% for women; 12.3% for men) and showed that disability significantly lowers the likelihood of economic activity (Bechange et al. 2024). Similarly, among 10,863 participants in rural Malawi, 9.6% reported a disability in at least one functional domain, with prevalence higher among women and older adults (Prynn et al. 2021). In Ghana, the 2017/18 Census of Agriculture found that 1.0% of male agricultural holders and 1.4% of female holders reported a disability, with sight and physical impairments being the most prevalent (GSS 2020). The state of disability in Ghana is further described based on the survey data.

Table 2 presents the prevalence and trends of disability among Ghanaian crop farmers for the 2012/13 and 2016/17 surveys, categorizing the data by disability types such as Physical, Sight, Hearing, Intellect, Speech, Emotional, and Other. This categorization facilitates a more nuanced understanding of the specific challenges that farmers with disabilities encounter in their agricultural production operations. The data on disability prevalence by crop shows distinct patterns, with millet and sorghum recording the highest overall prevalence rates of 0.116 and 0.112 respectively, whereas crops like eggplant exhibit the lowest of 0.048. This variation suggests that the experience of disability might differ significantly across agricultural contexts, reflecting diverse farming environments and possibly differing community support structures in regions predominantly cultivating these crops. Further analysis of the specific types of disability reveals more about the conditions affecting agricultural productivity. Physical disability is notably more common, as seen in the prevalence rates of millet (0.029) and sorghum (0.037), which could limit the ability of such persons to effectively undertake farm operations. Sight and hearing impairments also show significant rates, especially in millet (Sight: 0.027, Hearing: 0.014) and sorghum (Sight: 0.027, Hearing: 0.015). The lower incidence of reported intellectual (e.g., millet: 0.005, sorghum:

0.004) and emotional disabilities (e.g., millet: 0.004, sorghum: 0.004) may indicate either underreporting or a lack of adequate recognition and diagnostic facilities within rural agricultural communities. This discrepancy highlights the need for more inclusive health and support services that are sensitive to the full spectrum of disabilities, ensuring that all farmers receive the required assistance.

The analysis of the percentage change in headcount ratios for the survey periods for disability among crop farmers in Ghana as shown in Table 2 reveals a complex landscape with significant variations by crop and disability type. Notably, millet shows the largest increase in overall disability prevalence at 4.605%. Conversely, the general category of "Any crop" demonstrates a notable overall decrease in disability prevalence of 5.055%. Physical disability has increased notably among cocoyam farmers, rising by 2.194%. In terms of sensory disabilities, increases are observed in both sight and hearing categories; for instance, banana farmers reported increases in sight disability by 1.636% and hearing by 0.247%, pointing towards the need for enhanced medical support and adaptive technologies in these areas. Interestingly, intellectual and emotional impairments show smaller changes, often negative, as seen for cocoa where intellectual disability declined by 0.660%. Again, this may reflect variability in reporting and diagnosis of these types of disabilities or real changes in prevalence. Some crops, such as eggplant, displayed mixed trends with significant increases in speech disability (2.708%) alongside sharp declines in "Other" disabilities (-3.501%), underscoring the diverse effects of environmental or social factors on the prevalence of disability among farmers.

3. Methods

3.1 Conceptual framework

We conceptualize the effect of disability on farm performance along two dimensions: technical efficiency (TE) and technology gap ratios (TGRs). Disability can influence these outcomes through several interrelated pathways. With respect to TE, persons with disabilities (PWDs) often face reduced access to agricultural extension services due to both physical and attitudinal barriers within Ghana's extension delivery systems (Azumah and Zakaria 2020; Asante et al. 2024). Limited advisory access constrains knowledge of improved practices, resulting in suboptimal input use and lower efficiency. In addition, physical and environmental barriers such as reduced mobility, difficulty in supervising farm plots, and challenges with labor-intensive tasks delay critical operations like planting and weeding, further lowering efficiency (Bechange et al. 2024). Moreover, disability intensifies credit and input market frictions. Households with a member with disability in Ghana, for example, incur about 26 percent higher annual expenditures and face higher poverty rates (Asuman et al. 2021). These additional financial burdens reduce disposable income for investment in inputs and efficiency-enhancing technologies, thereby tightening liquidity constraints that systematically undermine efficiency.

Beyond efficiency within a given technology set, disability may also shape access to superior technologies and thus the technology gap ratio. Farmers with disabilities may be constrained to a lower technology frontier when adaptive tools, mechanization services, or disability-friendly ICT-based advisory systems are absent (Kachale et al. 2022). This widens the technology gap, implying that disability not only reduces efficiency within an existing frontier but also limits how close farmers can come to the best-practice technology available. Studies applying the metafrontier framework in Africa consistently reveal wide technology gaps between farmer groups and across agro-ecological zones (Abdulai et al. 2018; Coulibaly et al. 2020), suggesting that marginalized groups such as PWDs may be at an even greater disadvantage. The additional economic burden of disability highlighted by Asuman et al. (2021) reinforces this mechanism: by reducing the resources available for technology adoption, disability-related costs can trap PWDs in low-technology equilibria. Evidence further indicates that household-level disability in SSA is associated with lower effective farm labor, greater caregiving demands, and barriers to services and markets. These channels, documented across multiple settings, tend to reduce agricultural productivity unless countered by inclusive services and labor-saving or time-saving interventions (Bechange et al. 2024; UN Women 2024; Peprah et al. 2023; Sango et al. 2022). Based on this reasoning, we test two baseline hypotheses: that farmers with disabilities exhibit lower technical efficiency than those without disabilities (H1) and that they face larger technology gaps due to limited access to superior technologies (H2).

The extent of these disability effects is mediated by several contextual factors. Gender is especially important, as women with disabilities face a “double disadvantage” in accessing agricultural services and resources (Naami and Hayashi 2014). Type and severity of disability also matter, since mobility, vision, and hearing impairments impose different constraints. Age further influences the relationship: younger farmers with disabilities may be more able to cope physically with farming tasks, adopt assistive technologies, and respond to advisory services, whereas older PWDs may experience compounded constraints from declining health and higher household costs, leading to deeper efficiency losses. Education plays a similarly moderating role; better-educated PWDs are more likely to adopt improved practices and technologies, thereby narrowing both efficiency and technology gaps, while illiteracy may reinforce informational barriers. Crop characteristics are also critical. Cereal production typically requires labor-intensive land preparation and weeding, suggesting a stronger disability penalty, whereas perennial crops such as cocoa or cashew may involve less frequent but more specialized labor demands. Finally, agro-ecological conditions and infrastructure determine both the labor requirements and the technological options available. In areas with limited infrastructure and weak service delivery, disability-related disadvantages are likely to be magnified.

Globally, workers with disabilities earn about 12% less per hour than others, with roughly three-quarters of that pay gap unexplained by education, age, or job type (Ananian and Dellaferrera 2024). PWDs in developing countries face markedly lower labor market participation and are more likely to be self-employed or in informal work than formal employment (Mizunoya and Mitra 2013; Mitra and Sambamoorthi 2013). Disability-related employment gaps often tend to be more pronounced among men than women in these contexts, and the largest disparities are observed for individuals with multiple or severe disabilities (Mizunoya and Mitra 2013). This employment gap persists even after accounting for education and demographics, reflecting systemic barriers such as limited access to education and training, employer discrimination, inaccessible infrastructure, and weak enforcement of inclusive policies (Tripney et al. 2017; Acharya and Yang 2022; Mizunoya and Mitra 2013). These constraints not only restrict wage and self-employment opportunities but also reinforce economic vulnerability among PWDs, underscoring the need for targeted interventions to promote inclusive labor markets (Groce et al. 2011). Each study in this growing body of literature reinforces the need for targeted interventions to reduce the structural and attitudinal obstacles that PWDs face in the world of work.

3.2 Meta-stochastic frontier analysis

This study examines agricultural productivity differences between farmers with and without disabilities, focusing on two key components: (i) differences in technical efficiency and (ii) differences in technological endowments. To address these objectives, we apply the Meta-Stochastic Frontier (MSF) production function framework which permits us to compare farm performance both within and across groups operating under potentially different production technologies.

First, we estimate separate stochastic frontier production functions for farmers with and without disabilities. These group-specific frontiers allow us to compute technical efficiency (TE) scores, which reflect how efficiently each farmer converts inputs into output relative to others within their group. Second, we use the group frontiers to construct a metafrontier, representing the best feasible production technology available to all farmers in the sample. Comparing each group's frontier to this common benchmark yields technology gap ratios (TGRs), which measure how far each group's production technology lies below the metafrontier. These ratios represent relative technological endowments (Battese, Rao and O'Donnell 2004). Finally, we compute metafrontier technical efficiency (MTE) scores, which reflect each farmer's performance relative to the metafrontier. MTE combines both within-group efficiency and group-level technological constraints. This approach allows us to isolate and compare how much of the observed productivity gap is attributable to differences in technology access versus differences in how effectively farmers use the technologies available to them.

For each group, we assume a uniform farm production technology, which in conjunction with optimal management practices, position farmers at different points along their group-specific Stochastic Frontiers (SFs). Nonetheless, due to technical inefficiencies or unique disruptions, some farmers may perform below the SF. Additionally, instances of farmers outperforming the SF can occur, attributable solely to positive production shocks which are outside the control of the farmers. Following previous studies on crop production in Ghana which used the GLSS (Adaku et al. 2023; Ansah, Appiah-Twumasi and Tsiboe 2023; Asravor et al. 2024; Tsiboe, Aseete, et al. 2021), and due to its relative flexibility, this study implements the MSF after a statistical test reveals that the SF production function for the j^{th} group is specified as a Translog of the form:

$$f^j(x_{ijt}) = \ln y_{ijt} = \beta_{0r} + \sum_k \beta_{kj} \ln x_{kijt} + \frac{1}{2}\sum_s \sum_k \beta_{skj} log \ln x_{kijt} \ln x_{sijt} + \boldsymbol{\beta}_h \boldsymbol{h}_{ijt} + v_{ijt} - u_{ijt}$$

$$u_{ijt} \sim N^+[0, \exp(\boldsymbol{w}_{ijt}\boldsymbol{\alpha})], \qquad v_{ijt} \sim N(0, \sigma_{vj}^2) \tag{1}$$

where y_{ijt} represents the total value of crop production output for the i^{th} farmer in group j for survey t. Each x_{kijt} denotes the k^{th} input utilized by the i^{th} farmer, encompassing variables such as land, planting materials, both family and hired labor, fertilizer, and pesticide. In this framework, the group index j is defined by disability status, with j = 1 denoting farmers with disability and j = 0 denoting farmers without disability. Thus, disability does not appear as an explicit regressor in Equation (1), rather it governs group assignment and, in turn, the estimation of separate frontiers for each group. This setup allows us to capture differences in production technology and inefficiency attributable to disability status. The vector $\boldsymbol{h}_{ijt}$ contains production shifters for period (GLSS waves), location (ecological zone), and crops produced (proportion of area under listed crops with maize as the base). The terms u_{ijt} and v_{ijt} capture the deviations from the production frontier due to technical inefficiency and idiosyncratic shocks, respectively. A distinctive aspect of the model is the positive skewness assumption for u_{ijt}, suggesting that u_{ijt} could adhere to various distributions, including exponential, half-normal, gamma, and truncated-normal distributions, among others. After considering all potential distributions, we opted for a half-normal distribution (i.e., $u_{ijt} \sim N^+[0, \exp(\boldsymbol{w}_{ijt}\boldsymbol{\alpha}_j)]$), having encountered issues with convergence for other distributions in the case of sub-sample estimations. However, as will be shown later, our core findings for the full sample are generally robust to other commonly used distributions. We further assume that the deviation caused by technical inefficiency (u_{ijt}) is modeled as $\sigma_{u_{ijt}}^2 =$

$exp(\boldsymbol{w}_{ijt}\boldsymbol{\alpha}_j)$, where $\boldsymbol{w}_{ijt}$ includes covariates influencing technical inefficiency and $\boldsymbol{\alpha}$ represents a vector of parameters to be estimated. Following previous works (Adaku et al. 2023; Ansah et al. 2023; Asravor et al. 2024; Tsiboe, Aseete, et al. 2021), $\boldsymbol{w}_{ijt}$ contained farmer characteristics (age, education, and gender), institutional factors (land ownership, credit, mechanization, and extension), crop diversification, fixed effects for ecological zone and GLSS waves, and a constant term. Conversely, v_{ijt}, is assumed to follow a normal distribution with zero mean and variance, σ_v^2 [$v_{ijt} \sim N(0, \sigma_{vj}^2)$] (Belotti et al. 2013).

Given the SF production function for the *j*th group, the "pure farmer technical efficiency" (TE) of the *i*th farmer is calculated as:

$$TE_{ijt} = E\left[\exp(-u_{ijt}) \,|\, \hat{\varepsilon}_{ijt}\right] \quad (2)$$

To implement the two-step MSF method (Huang et al. 2014), we first separately estimated output levels for farmers with and without disabilities. Then, these outputs informed a pooled analysis in the MSF's second step. This process introduces a one-sided error term (u_{Mijt}) in the MSF, representing technology gaps associated with disability. Essentially, the MSF envelops all group-specific frontiers, allowing for a comprehensive examination of how agricultural productivity varies with disability status. The MSF [$f^M(x_{ijt})$] which envelops the group-specific stochastic frontiers [$f^j(x_{ijt})$] is specified in Equation (3) as:

$$f^M(x_{ijt}) = \ln \hat{y}_{ijt} = \beta_{0r} + \sum_k \beta_{kM} \ln x_{kiMt} + \frac{1}{2} \sum_s \sum_k \beta_{skM} log \ln x_{kiMt} \ln x_{siMt} + \boldsymbol{\beta}_h \boldsymbol{h}_{ijt} - u_{Mijt} \quad (3)$$

Where $u_{iM} \sim N^+(0, \exp(\boldsymbol{w}_i \boldsymbol{\alpha}_M))$ is strictly positive, implying that $f^j(x_{ijt}) \leq f^M(x_{ijt})$. Consequently, the ratio of group *j*'s stochastic frontier to the MSF is the technology gap ratio (TGR), which is represented as:

$$TGR_{ijt} = \frac{f^j(x_{ijt})}{f^M(x_{ijt})} = e^{-u_{iM}} \leq 1 \quad (4)$$

The TGR hinges on both the accessibility and level of adoption of agricultural technologies, which varies based on individual farm circumstances. The meta-technical efficiency (MTE) serves as an overarching performance metric, quantifying each farmer's technical efficiency relative to the meta-frontier production technology. Essentially, MTE is a composite measure that can be broken down into two components: TE, representing efficiency against group-specific frontiers, and the TGR, indicating the gap between the highest-performing technology available and the utilized technology set. Accordingly, each farmer's MTE is given by equation (5) as follows:

$$MTE_{ijt} = f^j(x_{ijt})\left[f^M(x_{ijt})e^{v_{ijt}}\right]^{-1} = TGR_{ijt} \times TE_{ijt} \quad (5)$$

The SF and meta-frontier parameters were estimated using maximum likelihood estimation. Input elasticities were derived as the first derivatives of these frontiers at mean input levels, and the production returns to scale (RTS) were calculated as the sum of these elasticities. Disability-specific TE, TGR, MTE were then calculated using designated equations, providing insights into differences in farm performance by disability status.

3.2 Forming comparable pairs of farmers

The debate over using self-reported health and disability indicators in economic and demographic research highlights a crucial methodological issue. These self-assessed measures are potent predictors for various outcomes (Stern 1989; Dwyer and Mitchell 1999; Benítez-Silva et al. 1999). They offer a comprehensive view of an individual's health and disability status, more so than what objective indices can provide, functioning almost as "sufficient statistics" with only slight enhancements from additional, objective measures (Benítez-Silva et al. 2004). Nonetheless, concerns about their vulnerability to bias and endogeneity are raised, especially the tendency of respondents to exaggerate their health problems (Lindeboom and Kerkhofs 2009; Kerkhofs and Lindeboom 1995). This issue introduces a classical endogeneity dilemma, casting doubt on the reliability of self-reported measures' predictive power. Therefore, the challenge involves carefully utilizing the rich information provided by self-reported indicators while implementing methodological controls to mitigate potential biases and ensure the integrity of research findings. Our study, relying on self-reported disability measures, addresses these concerns by utilizing a matched sample method to estimate the meta-frontier (Equation [3])—a common approach in studies using MSF that often encounter self-selection bias in technology adoption (Mayen, Balagtas and Alexander 2010; Crespo-Cebada, Pedraja-Chaparro and Santín 2014; Asmare, Jaraitė and Kažukauskas 2022; Bravo-Ureta et al. 2021; Tiedemann and Latacz-Lohmann 2013).

Our methodology pairs each farmer with disability with a farmer without disability of similar characteristics. Diverging from the traditional matching imputation (Abadie and Imbens 2006; Abadie and Imbens 2016) that replaces missing outcomes with those of a matched unit, our goal is to create a balanced sample for estimating the meta-frontier (Equation [3]). Matching criteria include farmer demographics (age, education, marital status, religion, ethnicity, and relation to the household head), household characteristics (size, dependency, and female ratio), crop diversification, share of land allocated to various crops, and land ownership. Importantly, our observations were paired strictly within the same operator gender, GLSS wave, region, ecology, and rural/urban locality. This careful matching allows us to better compare technological differences conditional on disability status, rather than to establish causality. We further acknowledge that unobserved factors—such as stigma, social capital, or underlying health conditions—may still influence both disability status and farm performance. While matching improves balance on observed characteristics, these unobserved factors cannot be fully accounted for and are therefore treated as a limitation of the study.

When matching farms for comparison, simplicity lies in having just one key covariate to consider, where each farm in the treatment group is paired with the closest non-treatment farm based on that single characteristic. However, the complexity escalates with an increase in the number and diversity (both scalar and categorical) of covariates to be matched on. To manage this complexity, we utilize one-to-one nearest-neighbor matching, establishing metrics of similarity to identify comparable pairs. Our metrics for determining the distance between pairs include options such as propensity scores (using Logit, Probit, Complementary log-log, or Cauchit link functions), Euclidean distance, Scaled Euclidean distance, Mahalanobis (Rubin 1980), or Robust Mahalanobis (Rosenbaum 2020; Rosenbaum 2010) distance. We provide a comprehensive analysis of the balancing diagnostics for these metrics in the appendix (Figure S1), where we examine standardized differences and variance ratios—the ideal values of which are close to zero for differences and close to one for ratios, aligning with literature benchmarks (Rubin 2001; Stuart 2010). From Tables S6-S7 and Figure S1, we find the robust Complementary Log-Log achieves the best balance regardless of the balancing diagnostic and the remainder of the manuscript relies on this matched data. Nonetheless, as will be shown later, our core findings for the full sample are generally robust to the other distance metrics.

We acknowledge, however, that matching can only adjust for observed heterogeneity. Unobserved factors—such as aspirations, motivation, or innate ability—may still bias the results, particularly if they correlate with both disability status and productivity outcomes. While more advanced stochastic frontier approaches (e.g., Greene 2010) could in principle address such concerns, these require valid exclusion restrictions (instruments that predict disability but not production), which are unavailable in the GLSS data. Moreover, such models are more suited for analyzing adoption of specific technologies (e.g., irrigation or hybrid seeds) rather than embodied characteristics like disability. For transparency, we therefore treat our results as associational rather than causal and explicitly acknowledge this limitation in the conclusion.

To estimate standard errors, we utilized a jackknife resampling technique. This involved creating 100 resampled datasets by systematically excluding one Enumeration Area (EA) from each survey in every resampling iteration, effectively pooling the remaining EAs from all surveys for each iteration. This process was conducted independently for each survey. For each of the 100 unique resampled datasets, we estimate the Equation (1), match the data, and estimate the Equation (3) while incorporating the correction for monotonicity and quasi-concavity when estimating Equations (1) and (3). The variability of our estimates across the resampled datasets was used to calculate the standard errors for estimated parameters and effects.

4. Results and discussion

4.1 Diagnostic tests

After ensuring that our estimated Translog models adhere to the monotonicity and curvature conditions for a well-behaved production function, the results displayed in Table 3 indicate that only 23-49% and 21% of observations, respectively, satisfied these constraints. Despite these limitations at the observation level, the overall positive sign of the elasticities across the sample suggests that, on average, our models exhibit appropriate behavior. This general adherence to expected economic principles demonstrates the robustness of our analytical approach in capturing the dynamics of agricultural production in Ghana. Next, three tests were performed to verify the skewed error specification, which is central to the MSF approach, including the one-sided generalized likelihood-ratio test for technical inefficiency (Gutierrez, Carter and Drukker 2001) and two skewness tests of the residuals resulting from an OLS estimation (Schmidt and Lin 1984; Coelli 1995). These test results were rejected; thus, the study proceeds with the MSF approach. Furthermore, the likelihood ratio test for the null hypothesis that farmers with and without disabilities share similar production frontiers was rejected, which supports the fact that farmers in both groups in Ghana operate under heterogeneous technologies and thus, their production performance cannot be compared using the SF estimates.

Table 3 also indicates that the mean of the proportion of crop production variance due to technical inefficiency [$\gamma = \sigma_u^2/\sigma^2$] averaged 0.295 and 0.317 for farmers with and without disabilities, respectively. Since all these ratios are less than 0.50, they suggest that a considerable amount of the observed variation in crop output could not be attributed to the inefficient use of farm inputs but rather to idiosyncrasies such as biotic and abiotic shocks, statistical errors in data measurement, and model specifications. The mean of the estimated γ for the meta-frontier was 0.99, implying that a large proportion of the observed variation in crop output, given the disability and non-disability frontiers, could be attributed to technological gaps.

4.2 Output elasticities

Table 3 illustrates that the responsiveness of total crop output to each factor input is statistically significant at the 1% significance level and consistently shows positive correlations across all models, echoing the findings of several studies in Ghana (Asravor et al. 2024; Tsiboe et al. 2022; Ansah et al. 2023; Adaku et al. 2023). In these models, land consistently exerts the largest effect on total farm output, followed sequentially by family labor, planting materials, fertilizer, hired labor, and pesticide. When disaggregated by disability status, the results show slightly lower returns to land for PWDs (0.561) than for farmers without disabilities (0.608), albeit this difference is not statistically significant.

In contrast, the elasticities of planting material, family labor, hired labor, fertilizer, and pesticide are marginally higher for farmers with disabilities than for those without disabilities, but the returns to all of these inputs are not statistically significant except for pesticide. For pesticide, a clear and statistically significant difference emerges, with an elasticity of 0.017 for PWDs relative to 0.011 for farmers without disabilities. This significant returns on pesticide use for PWDs may stem from their quest to make judicious use of chemical inputs to compensate for physical limitations in performing labor-intensive tasks such as pest and weed controls and thus, tend to gain more from such inputs than their peers. These elasticity estimates suggest that, despite challenges, farmers with disabilities generally tend to make more productive use of their accessible inputs than their counterparts, highlighting the potential for PWDs to significantly contribute to agricultural productivity growth in Ghana when adequately supported. Lastly, the returns to scale for PWDs (0.899) is slightly lower than that of their peers without disabilities (0.911). This indicates that both groups are approaching constant returns to scale, though farmers with disabilities are marginally less efficient at scaling their operations.

The matched sample estimates under the meta-frontier provide useful insight into how crop mix contributes to output disparities between farmers with and without disabilities. For high-value crops such as cocoa and peanuts, both groups benefit from significant positive effects, but the magnitude is higher for PWDs (e.g., cocoa coefficient of 1.305 vs. 1.236 for farmers without disability), suggesting that when PWDs are engaged in cash crop production, the value of their output rises proportionally more. However, for staple crops such as cassava, plantain, sorghum, and beans, the negative coefficients are larger in absolute value for PWDs compared to their peers (e.g., beans –0.338 vs. –0.206), suggesting that PWDs face sharper value shortfalls when cultivating low-value staples. Together, these patterns suggest that crop composition amplifies productivity gaps: while cultivating cocoa and other high-value crops can partly offset disadvantages, PWDs are generally more constrained in achieving value gains from staple production.

4.3 Technology adoption and technical efficiency

The level of technological endowment of farmers with and without disability, which is represented by the estimated technology gap ratios (TGRs) is summarized in Table 3. Findings from the matched sample reveal an average TGR of 0.818 and 0.931 for farmers with and without disabilities, respectively. This implies that farms managed by people with and without disabilities generally produce, on average, 82 and 93% of the potential industrial output, respectively. This culminates into a difference of 11[2] percentage points disability-associated technology gaps in crop production in Ghana. Consequently, to rake in the same level of farm output as their peers, farmers with disabilities may have to raise their extant level of farm technology by an average of 11 percentage points. This result reflects the considerable barriers faced by PWDs in accessing productive technologies, which in turn limit their capacity to effectively compete with farmers without disabilities.

Evaluating the performance of each farmer group relative to its own technology, as captured by the pure farmer technical efficiency (TE) index, reveals an average score of 0.78 for both groups. This indicates that, on average, farms managed by people with and without disabilities each attain about 78% of their respective potential frontier output, given their current farm-specific technologies. This is not surprising, as farmers with disabilities typically have significantly larger household sizes and depend more heavily on household labor (Table 1) than those without

[2] *Difference in mean TGR between farmers with disabilities and those without disabilities multiplied by 100.*

disabilities. This finding aligns with recent empirical studies focusing on Ghana in particular, and Africa more generally (Asravor et al. 2024, 2025; Ansah et al. 2023; Adom and Adams 2020; Mugera and Ojede 2014), which reveal that smallholder farmers in developing countries generally produce beneath their technically efficient frontiers.

Combining the TGR and TE effects into a single comparable measure (meta-frontier technical efficiency [MTE = TE × TGR] scores) across both groups shows that farmers with and without disability operate at 63 and 72.5% of the industrial frontier, respectively. This corresponds to a statistically significant MTE difference of 9.5%, indicating that farmers with disabilities are generally 9.5 percentage points less efficient in their production operations than those without disabilities. Since both groups exhibit similar TE scores relative to their group-specific frontiers, the observed heterogeneity in MTE between them can be attributed entirely to disability-driven differences in technological endowments.

The disability gap of approximately 11 percentage points in technology access can partly be attributed to the significant obstacles faced by PWDs in accessing farm inputs and institutional support. For instance, in Zimbabwe, PWDs encounter political and structural barriers that limit their access to land and agrarian support (Tom 2024). Similarly, in Nigeria, PWDs report inadequate access to appropriate technology, highlighting systemic issues that hinder their participation in social and economic activities (Ogunjimi et al. 2020). In Ghana, PWDs face considerable barriers, including difficulties in accessing farmlands, farming tools, credit and negative societal attitudes, which tend to limit their inclusion and participation in farming (Agyei-Okyere et al. 2019; Peprah et al. 2023). According to the recent census of agriculture in Ghana, PWDs are often disadvantaged in terms of ownership and access to productive assets such as land and other properties, which considerably limit their ability to engage in farming (GSS, 2023). In

Figure 1 from our sample, which is presented in the appendix and based on the matched dataset, we find that disability status significantly influences the usage rates of various crop production inputs. Notable correlations between disability and agricultural production inputs include decline in the per hectare use of fertilizer (-46%), planting materials (-45%), pesticide (-38%), and hired labor (-28%). Conversely, the difference in landholdings between farmers with and without disabilities is statistically similar. These outcomes suggest that the disability of farmers and their household members significantly influences their crop production technology mix relative to their intensive margin.

Access to agricultural inputs by PWDs can be significantly limited by financial constraints, as evidenced by various studies. In Uganda, barriers to microcredit access for farmers with disabilities include exclusion by staff and non-disabled members of credit groups, self-exclusion, exclusion by credit design, and disability itself, with credit design being the most significant obstacle (Beisland and Mersland 2012a). Similarly, in Ghana, research indicates that having disabilities reduces the likelihood of accessing and using formal financial institutions, with PWDs being significantly less likely to use commercial and rural banks (Peprah et al. 2023). However, they are more likely to utilize mobile money services (Peprah et al. 2023). Additionally, PWDs tend to rely more on informal self-help schemes than formal microfinance services, accessing more savings than loans (Beisland and Mersland 2012b). Financial barriers highlight the systemic challenges that PWDs face in accessing the necessary resources to fully participate in agricultural activities.

4.4 Robustness of main findings

Next, we evaluate the robustness of the observed disability gap in crop production linked to technological endowment across various dimensions of the empirical analysis. First, we consider the measure of disability. In our main specification, a farmer's disability status was broadly defined to include the farmer, their immediate family (spouse and children), and other household members. When we narrowly restrict the disability indicator to the exclusive disability of individual household members, Table 4 shows that the observed disability gap in technology access persists, with levels varying from +16% for household members other than the spouse or child to -24% for the child (adopted or biological) of the farmer. However, when examining TE, significant differences emerge, unlike the case of the broadly defined indicator where the difference was insignificant. Specifically, we find that a farmer with a disabled spouse or household member other than the spouse or child has a TE that is 26% and 18% lower than the base category (farmer without any disabled individual in their household), respectively. Conversely, compared to the base category, we find higher TE scores when the disability exclusively includes only the child (adopted or biological) of the farmer (18%) or only the spouse or child of the farmer (2%).

Ultimately, regardless of the divergence in the exclusively estimated gaps in TGR and TE from the broadly defined ones, we observe MTE gaps ranging from -27% (farmer only disability) to -8% (household member other than spouse or child). These exclusively estimated MTE gaps are statistically like the broadly defined gap of -13%, highlighting that while the overall observed shortfall in crop production is robust regardless of whose disability is considered, the source (TGR vs TE) of this shortfall depends on who's disability we focus on. In cases where "child (adopted or biological) of the farmer only" and "spouse or child of the farmer only" are disabled, production gains tied to relatively higher TE for PWDs are eroded by substantially larger gaps in technology access (TGR). For all other exclusive disabilities, both TE and TGR contribute to the shortfall, with the former being more prominent. These diverging results suggest that targeted interventions to address both technological access and technical efficiency shortfalls are essential, particularly when considering the disability of specific members of the household.

When disability is kept as broadly defined to include all household members, our core findings on the gaps in TGR, TE, and MTE remain robust across various dimensions: (1) the choice of production function, distributional assumption on the inefficiency term, calculation method for observational level scores (TGR, TE, and MTE), central tendency estimation of observational level scores, matching algorithm, and whether the production function is restricted or freely estimated (see Figure S2). The only exception is when we use a Rayleigh distribution for the inefficiency term, where we find relatively higher gaps against PWDs in MTE and TGR but a positive differential in TE, albeit statistically like the preferred assumption of a half-normal distribution. Other notable exceptions include relatively higher gaps in MTE when an unrestricted production function is estimated and when observational level values are aggregated by taking the median. Overall, the pattern of results from the robustness checks in Tables 3 and S2 are consistent with the main findings.

4.5 Observed heterogeneity

Figures 2 and 3 report the disability gap in TGR, TE, and MTE across various observable characteristics, including farmer's gender, age, education, crop produced, and regional location. For each dimension of heterogeneity, we summarize the observation level TGR, TE, and MTE estimated using the entire matched sample, without implementing separate MSF along the disability dimension for each level of a given heterogeneity variable. We find that the disability gap in crop production and its attribution do not significantly change by gender or age, except for farmers over 59 years old and those with senior secondary school education, where the disability gap is smaller due to notable gains in TE. At the crop level, the disability gap in MTE against PWDs is robust across all crops, with the highest gaps observed in oil palm (-30.35%), followed by okra (-22.84%), pepper (-20.53%), cocoyam (-19.63%), beans (-19.06%), rice (-17.15%), sorghum (-15.88%), palm (-15.51%), other (-15.5%), millet (-15.12%), yam (-13.21%), peanut (-13.07%), plantain (-12.37%), tomato (-12.02%), cassava (-11.79%), maize (-11.27%), cocoa (-7.16%). Regional differences show the highest disability gap in Upper East (-17.55%), Upper West (-14.55%), Northern (-14.55%), Western (-12.02%), Central (-11.65%), Greater Accra (-11.63%), Eastern (-11.46%), Brong-Ahafo (-9.79%), Volta (-9.27%), Ashanti (-8.45%).

5. Conclusion

In this paper, we extend the literature on productivity analysis by accounting for the disparity in technology usage and crop production efficiency between farmers with and without disability in Ghana. Most of the empirical studies on productivity analysis have been very insightful and informative. However, the role of disability in agricultural production is less explored, especially in the era of changing demographics, discrimination, unemployment, and broader societal hardships faced by PWDs. This study employs the meta-stochastic frontier analysis and matching techniques on farm-level data for 2012/13 and 2016/17 to assess the degree of disparity in agricultural technology level and technical efficiency based on disability and further explore how this disparity varies based on different demographics and agricultural contexts. We find that, relative to their group-specific frontiers, technical efficiency levels are nearly identical for farmers with and without disabilities, with differences of less than 0.5%. This suggests that, when given equal access to resources, farmers with disabilities are just as efficient as those without disabilities. However, the study also uncovers a significant disparity in the productive capacity of technologies used by PWDs, which is about 11 percentage points lower than that of those without disabilities. This results in a 9.5% production disadvantage against farmers with disabilities.

This production gap among PWDs primarily stems from their limited access to essential advisory services and agricultural inputs like planting materials, labor, fertilizer, and agro-chemicals. This observed disability technology gap highlights not only deep structural inequalities but also clear entry points for targeted policies and strategic interventions. Efforts aimed at bridging this gap should move beyond general advocacy toward practical measures that improve both inclusivity and productivity among farmers with disabilities. Policymakers and development practitioners can act in several ways. First, agricultural support programs, such as input subsidies, credit schemes, and technology dissemination initiatives should explicitly include accessibility criteria to ensure that farmers with disabilities can fully participate in such programs. Second, extension services and training programs need to adapt their delivery methods and materials to accommodate diverse physical, intellectual, cognitive, and sensory abilities, including the use of assistive technologies such as adapted farming equipment. Third, investments in rural infrastructure and market facilities should adopt inclusive design principles to eliminate the physical barriers that limit participation. Finally, mainstreaming disability into Ghana's agricultural policy frameworks and fostering collaboration between the Ministry of Food and Agriculture (MoFA), the National Council for Persons with Disability (NCPD), and local organizations will ensure that inclusion is both institutionalized and sustained. Addressing these vital issues will promote social inclusion by integrating PWDs into the productive economy, enhance overall agricultural efficiency and growth in Ghana where agriculture remains central to livelihoods, and further align with international commitments to equitable and sustainable development under the Sustainable Development Goals.

Some caveats to the analysis are worth mentioning. First, the study faced challenges in identifying suitable instruments that met the exclusion restriction criteria, leading to the use of matching techniques instead of an ideal instrumental variable. Matching improved balance and comparability between farmers with and without disabilities, reducing reliance on the model's functional form and diminishing the effects of omitted variable bias. Thus, the findings should be viewed as a detailed examination of the relationship between disability and production rather than a definitive demonstration of causality. Second, the definition of disability status was broad, encompassing not only the farmer but also immediate family members (spouses and children) and other household members. Although we applied more narrowly defined statuses in robustness checks, this broad definition remains important to keep in mind when interpreting our results, as the household member affected by disability and their relationship to the farmer can influence which interventions are most appropriate.

Third, the study relies on repeated cross-sectional data, which prevents tracking the same farmers across survey waves. While we mitigated this by controlling survey-specific effects and restricting matching within waves, the pooled-sample approach cannot fully eliminate differences in survey design, context, or respondent composition. The results should therefore be interpreted as reflecting population-level associations rather than individual-level dynamics. Fourth, although we distinguished between farmers with and without disabilities, we could not further disaggregate by specific disability traits. As shown in Table 2, the prevalence of individual disability types is very low (ranging from about 0.2% to 3.7% across crops and disability types), resulting in sub-samples too small for stable estimation of trait-specific frontiers. This means our analysis may not capture the full heterogeneity or potential scale effects across disability types. Again, since our disability variable captures current activity-limiting conditions rather than disability history, it does not distinguish between early- and later-onset disability. If early-onset disability influenced some of the covariates used in the matching exercise, our estimates may understate the true disability gap. As such, the reported differences should be viewed as conservative, reflecting lower-bound estimates of the effect of disability on production. Finally, since we do not have appropriate instruments such as data on input prices to deal with potential concerns of endogeneity, there could be endogeneity of input choices. Future studies should explicitly address this by collecting the relevant data needed to construct suitable instruments.

Despite these limitations, the findings of this study underscore the urgent need for targeted policy interventions to close the technology gap and ensure equitable access to agricultural inputs for farmers with disabilities. Such measures are essential not only for advancing social justice but also for fostering a more productive and resilient agricultural sector in Ghana and across the broader sub-Saharan African region. By addressing these disparities, we can move closer to achieving sustainable agricultural development that benefits all members of society, regardless of physical abilities.

References

Abadie, A., and G.W. Imbens. 2006. "Large sample properties of matching estimators for average treatment effects." *Econometrica* 74(1):235–267.

Abadie, A., and G.W. Imbens. 2016. "Matching on the estimated propensity score." *Econometrica*.

Abdul Karimu, A.T.F., D.M., Mont, and Z.A. Morris. 2024. "The experience of persons with disabilities as beneficiaries of Ghana's District Assemblies Common Fund." *PLoS One* 19(4):e0297845.

Abdulai, S., A. Zakariah, and S.A. Donkoh. 2018. "Adoption of rice cultivation technologies and its effect on technical efficiency in Sagnarigu District of Ghana." *Cogent Food and Agriculture* 4(1):1424296.

Acharya, Y., and D. Yang. 2022. "The effect of disability on educational, labor market, and marital outcomes in a low-income context." *SSM Population Health* 19:101155.

Adaku, A.A., F. Tsiboe, and J. Clottey. 2023. "Taking stock of gender gaps in crop production technology adoption and technical efficiency in Ghana." *Agrekon* 63:31-48.

Adom, P.K., and S. Adams. 2020. "Decomposition of technical efficiency in agricultural production in Africa into transient and persistent technical efficiency under heterogeneous technologies." *World Development* 129:104907.

Agyei-Okyere, E., W. Nketsia, M.P. Opoku, E.L. Torgbenu, B.A. Alupo, and L. Odame. 2019. "Sustainable employment opportunities for persons with disabilities in Ghana: Exploring perceptions and participation in agriculture." *Business Strategy and Development* 2(2):68–76.

Ananian, S., and G. Dellaferrera. 2024. "A study on the employment and wage outcomes of people with disabilities." ILO Working Paper 124. Geneva: International Labour Office.

Ansah, I.G.K., M. Appiah-Twumasi, and F. Tsiboe. 2023. "Starchy staples production shortfalls in Ghana: Technical inefficiency effects outweigh technological differences across ecologies." *PLOS ONE* 18(4):e0284780.

Asante, I. K., J. K. Ocran, A. Awini, E.T.K. Ametepey, and G. Owusu. 2024. "Empowering farmers with disabilities in Ghana: Tailored agricultural extension advisory services." *International Journal of Agricultural Extension* 12(2):153–171.

Asmare, F., J. Jaraitė, and A. Kažukauskas. 2022. "Climate change adaptation and productive efficiency of subsistence farming: A bias-corrected panel data stochastic frontier approach." *Journal of Agricultural Economics* 73(3):739–760.

Asravor, J., F., Tsiboe, A., Adetoyinbo, and J. Ankamah. 2025. "Charting the path to increased oil palm output in Ghana beyond area expansion: Technology or managerial capacity—Which leads the way? " *Agribusiness*. https://doi.org/10.1002/agr.22054.

Asravor, J., F. Tsiboe, R.K. Asravor, A.N. Wiredu, and M. Zeller. 2024. "Technology and managerial performance of farm operators by age in Ghana." *Journal of Productivity Analysis* 61(3):279–303.

Asravor, J., A. Wiredu, K. Siddig, and E. Onumah. 2019. "Evaluating the Environmental-Technology Gaps of Rice Farms in Distinct Agro-Ecological Zones of Ghana." *Sustainability* 11(7):2072.

Asuman, D., C.G. Ackah, and F. Agyire-Tettey. 2021. "Disability and household welfare in Ghana: Costs and correlates." *Journal of Family and Economic Issues* 42(4):633–649.

Azumah, S.B., A. Zakaria, and N.A. Boatengn. 2020. "Modelling rice farmers subscription to agricultural extension methods in Ghana." *Review of Agricultural and Applied Economics* 23(1):47-54.

Bairwa, R.C., M.L. Meena, G.S. Dangayach, and R. Jain. 2022. "Prevalence of musculoskeletal disorders among the agricultural workers: A review." In D. Chakrabarti, S. Karmakar, and U. R. Salve, eds. *ergonomics for Design and Innovation*. Cham: Springer International Publishing, pp. 439–446.

Bannink Mbazzi, F., S. Hameed, J.K. Ganle, T. Shakespeare, and S. Polack. 2024. "Participatory research with youth with disabilities: Experiences from sub-Saharan Africa." *African Journal of Disability* 13(0):a1491.

Battese, G.E., D.S.P. Rao, and C.J. O'Donnell. 2004. "A Metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies." *Journal of Productivity Analysis* 21(1):91–103.

Bechange, S., E. Jolley, A. Jeyam, G. Okello, B. Wekesa, and E. Schmidt. 2024. "Disability and labour market participation among smallholder farmers in Western Kenya." *PLoS One* 19(7):e0306458.

Beisland, L.A., and R. Mersland. 2012a. "Barriers to microcredit for disabled persons: Evidence from economically active persons in Uganda." *Enterprise Development and Microfinance* 23(1):11–24.

Beisland, L.A., and R. Mersland. 2012b. "The use of microfinance services among economically active disabled people: Evidence from Uganda." *Journal of International Development* 24(S1):S69–S83.

Bell, A.R., B.K., Jack, P., Oliva, C., Severen, and T. F. Walker. 2015. "The timing and effectiveness of subsidies for agricultural technology adoption: Evidence from Malawi." Cambridge, MA: Abdul Latif Jameel Poverty Action Lab (J-PAL) and Innovations for Poverty Action (IPA). Available at: https://www.povertyactionlab.org/evaluation/timing-and-effectiveness-subsidies-agricultural-technology-adoption-zambia [Accessed October 16, 2025].

Belotti, F., S. Daidone, G. Ilardi, and V. Atella. 2013. “Stochastic frontier analysis using Stata.” *The Stata Journal* 13(4):719–758.

Benítez-Silva, H., M. Buchinsky, H. Man Chan, S. Cheidvasser, and J. Rust. 2004. “How large is the bias in self-reported disability?” *Journal of Applied Econometrics* 19(6):649–670.

Benítez-Silva, H., M. Buchinsky, H.M. Chan, J. Rust, and S. Sheidvasser. 1999. “An empirical analysis of the social security disability application, appeal, and award process.” *Labour Economics* 6(2):147–178.

Bravo-Ureta, B.E., M. González-Flores, W. Greene, and D. Solís. 2021. “Technology and technical efficiency change: Evidence from a difference in differences selectivity corrected stochastic production frontier model.” *American Journal of Agricultural Economics* 103(1):362–385.

Centers for Disease Control and Prevention (CDC). (2022). “*Disability and health data system (DHDS): Disability and age.*” *Atlanta, GA: CDC.* Available at: *https://www.cdc.gov/ncbddd/disabilityandhealth/dhds/index.html* [Accessed Augst 6, 2025].

Coelli, T. 1995. “Estimators and hypothesis tests for a stochastic frontier function: A Monte Carlo analysis.” *Journal of Productivity Analysis* 6(3):247–268.

Coulibaly, M. 2020. “Effects of information and communication technologies on the banks’ production level in West African Economic and Monetary Union.” *Journal of Economics and Sustainable Development* 11(12):2222-2855.

Crespo-Cebada, E., F. Pedraja-Chaparro, and D. Santín. 2014. “Does school ownership matter? An unbiased efficiency comparison for regions of Spain.” *Journal of Productivity Analysis* 41(1):153–172.

Dwyer, D.S., and O.S. Mitchell. 1999. “Health problems as determinants of retirement: Are self-rated measures endogenous?” *Journal of Health Economics* 18(2):173–193.

Ehlers, S.G., and W.E. Field. 2019. “Accessing and operating agricultural machinery: Advancements in assistive technology for users with impaired mobility.” *Assistive Technology* 31(5):251–258.

FAO, IFAD, and WFP. 2013. “*The State of Food Insecurity in the World 2013. The multiple dimensions of food security*.” Rome, Italy: Food and Agriculture Organization of the United Nation, FAO. Available at: http://www.fao.org/publications/sofi/2013/en/ [Accessed July 16, 2024].

Field, W.E., and P. Jones. 2006. “Disability in Agriculture.” In J. E. Lessenger, ed. *Agricultural Medicine: A Practical Guide*. New York, NY: Springer, pp. 70–80. Available at: https://doi.org/10.1007/0-387-30105-4_7 [Accessed July 16, 2024].

Gaiha, R., S. Mathur, and V.S. Kulkarni. 2022. "Rural poverty and disability in Ethiopia: Formidable policy challenges." *Journal of Policy Modeling* 44(5):1000–1015.

Ghana Statistical Service (GSS). 2020. "Ghana 2017/18 Census of Agriculture: Gender in agriculture thematic report." Accra: GSS. Available at: *chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://statsghana.gov.gh/gssmain/fileUpload/Agriculture%20&%20Environment/Gender%20in%20Agriculture.pdf* [Accessed July 16, 2025].

Groce, N., M. Kett, R. Lang, and J.F. Trani. 2011. "Disability and poverty: The need for a more nuanced understanding of implications for development policy and practice." *Third World Quarterly* 32(8):1493–1513.

Gutierrez, R.G., S. Carter, and D.M. Drukker. 2001. "On boundary-value likelihood-ratio tests." *Stata Technical Bulletin* 10(60). Available at: https://econpapers.repec.org/article/tsjstbull/y_3a2001_3av_3a10_3ai_3a60_3asg160.htm [Accessed October 21, 2017].

Hota, S., V.K. Tewari, L.K. Dhruw, and A.K. Chandel. 2023. "A sensor-based assistive technology for lower-limb-disabled agricultural workers and abled female workers for tractor clutch and brake operation." *Journal of Field Robotics* n/a(n/a). Available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/rob.22214 [Accessed July 16, 2024].

Huang, C.J., T.-H. Huang, and N.-H. Liu. 2014. "A new approach to estimating the metafrontier production function based on a stochastic frontier framework." *Journal of Productivity Analysis* 42(3): 241–254.

International Labour Organization (ILO). 2019. "*Disability and work: A global perspective.*" *Geneva: International Labour Office.* Available at: *https://www.ilo.org/topics-and-sectors/disability-and-work* [Accessed on August 10, 2025].

International Labour Organization (ILO). 2022. "*New ILO database highlights labour market challenges of persons with disabilities.*" Available at: *https://ilostat.ilo.org/new-ilo-database-highlights-labour-market-challenges-of-persons-with-disabilities/* [Accessed on October 10, 2025].

Jenkins, P.L., G. Earle-Richardson, E.M. Bell, and J.J. May. 2012. "Prevalence of disability in U.S. farm families." *Disability and Health Journal* 5(3):192–198.

Kachale, F., I. Mahaka, F. Mhuriro, M. Mugambi, J. Murungu, B. Ncube, ... and K. Segal. 2022. "Integration of HIV prevention and sexual and reproductive health in the era of anti-retroviral-based prevention: Findings from assessments in Kenya, Malawi and Zimbabwe." *Gates Open Research*, 5:145.

Kerkhofs, M., and M. Lindeboom. 1995. "Subjective health measures and state dependent reporting errors." *Health Economics* 4(3):221–235.

Kuyini, A.B., A.-R.K. Alhassan, and F.K. Mahama. 2011. “The Ghana community-based rehabilitation program for people with disabilities: what happened at the end of donor support?” *Journal of Social Work in Disability and Rehabilitation* 10(4):247–267.

Lindeboom, M., and M. Kerkhofs. 2009. “Health and work of the elderly: subjective health measures, reporting errors and endogeneity in the relationship between health and work.” *Journal of Applied Econometrics* 24(6):1024–1046.

Mayen, C.D., J.V. Balagtas, and C.E. Alexander. 2010. “Technology adoption and technical efficiency: Organic and conventional dairy farms in the United States.” *American Journal of Agricultural Economics* 92(1):181–195.

Mishra, A., and J. Narayan. 2024. “Health care for persons with intellectual and developmental disabilities in India.” *Journal of Policy and Practice in Intellectual Disabilities* 21(1):e12484.

Mitra, S., and U. Sambamoorthi. 2008. “Disability and the rural labor market in India: Evidence for males in Tamil Nadu.” *World Development* 36(5):934–952.

Mitra, S., and U. Sambamoorthi. 2013. “Disability prevalence among adults: Estimates for 54 countries and progress toward a global estimate.” *Disability and Rehabilitation* 36(11): 940–947.

Mizunoya, S., and S. Mitra. 2013. “Is there a disability gap in employment rates in developing countries? ” *World Development* 42:28-43.

MoFA. 2015. “Gender and agricultural development strategy II”. Ministry of Food and Agriculture (MoFA), Accra, Ghana. Available at: https://faolex.fao.org/docs/pdf/gha191457.pdf [Accessed November 13, 2025].

MoFA. 2025. “Feed Ghana programme (FGP). A four-year agricultural transformation programme (2025 - 2028).” Ministry of Food and Agriculture (MoFA), Accra, Ghana. Available at: https://mofa.gov.gh/site/images/pdf/Feed_Ghana_Programme.pdf [Accessed November 03, 2025].

Mont, D., and C. Nguyen. 2018. “Spatial variation in the poverty gap between people with and without disabilities: Evidence from Vietnam.” *Social Indicators Research* 137(2):745–763.

Mugera, A., and A. Ojede. 2014. “Technical efficiency in African agriculture: Is it catching up or lagging behind?” *Journal of International Development* 26(6):779–795.

Naami, A., and R. Hayashi. 2014. “Empowering women with disabilities in northern Ghana.” *Review of Disability Studies: An International Journal* 7(2).

Njuki, E., M.A., Lachaud, B.E., Bravo-Ureta, and N. Key. 2025. Ethnic and Gender disparities in U.S. agriculture: An analysis of technology and technical efficiency differentials. *American Journal of Agricultural Economics*, 107(4):993–1015.

O’Donovan, M.-A., and E.L. Whittle. 2024. “Housing, homelessness and disability: The Commodification of a core human right and breach of this right for people with disability.” *Advances in Neurodevelopmental Disorders* 8(1):141–150.

Ogunjimi, S.I., A. Temidayo, A.A. Oladayo, and A. Adesoji. 2020. “Accessibility of people with disabilities to productive resources in Nigeria: Dream or reality.” *Journal of Disability Studies* 6(2):65–69.

Opoku, M.P., W. Nketsia, E. Agyei-Okyere, and W.K. Mprah. (2018). Extending social protection to persons with disabilities: Exploring the accessibility and the impact of the Disability Fund on the lives of persons with disabilities in Ghana. *Global Social Policy* 19(3), 225-245.

Opoku, M.P., J-F.K. Swabey, D. Pullen, and T. Dowden. 2019. “Poverty alleviation among persons with disabilities via United Nations’ sustainable development goals in Ghana: Voices of stakeholders with disabilities.” *Sustainable Development* 27(1):175–182.

Oteng, C., and P. Gamette. 2024. “Energy inclusiveness intensity among persons with disability: Evidence from an Emerging Crude Oil Producing Country.” *The Extractive Industries and Society* 17:101406.

Owusu, V., E. Donkor, and E. Owusu-Sekyere. 2018. “Accounting for the gender technology gap amongst smallholder rice farmers in Northern Ghana.” *Journal of Agricultural Economics* 69(2):439–457.

Palmer, M., J. Williams, and B. McPake. 2019. “Standard of living and disability in Cambodia.” *The Journal of Development Studies* 55(11):2382–2402.

Peprah, J.A., E.A. Avorkpo, and E. Kulu. 2023. “People with disability and access to financial services: Evidence from Ghana.” *Regional Science Policy and Practice* 15(6):1198-1216.

Prynn, J.E., A. Dube, E. Mwaiyeghele, O. Mwiba, S. Geis, O. Koole, M. Nyirenda, H. Kuper, and A.C. Crampin. 2021. “Self-reported disability in rural Malawi: Prevalence, incidence, and relationship to chronic conditions.” *Wellcome Open Research* 4(90):15196.5.

Rana, M.S., M.B. Alam, S.J. Khanam, M.I. Kabir, G. Khandaker, and M.N. Khan. 2024. “Prevalence and patterns of comorbidities in people with disabilities and their associated socio-demographic factors.” *Scientific Reports* 14(1):1425.

Rosenbaum, P.R. 2010. “*Design of Observational Studies*.” New York, NY: Springer. Available at: https://link.springer.com/10.1007/978-1-4419-1213-8 [Accessed December 13, 2023].

Rosenbaum, P.R. 2020. “Modern algorithms for matching in observational studies.” *Annual Review of Statistics and Its Application* 7(1):143–176.

Rowland, M., J. Peterson-Besse, K. Dobbertin, E.S. Walsh, W. Horner-Johnson, and Expert Panel on Disability and Health Disparities. 2014. “Health outcome disparities among subgroups of people with disabilities: A scoping review.” *Disability and Health Journal* 7(2):136–150.

Rubin, D.B. 1980. “Bias reduction using Mahalanobis-Metric Matching.” *Biometrics* 36(2):293–298.

Rubin, D.B. 2001. “Using propensity scores to help design observational studies: Application to the tobacco litigation.” *Health Services and Outcomes Research Methodology* 2(3–4):169–188.

Samuel, L.J., J. Zhu, P. Dwivedi, E.A. Stuart, S.L. Szanton, Q. Li, R.J. Thorpe, N.S. Reed, and B.K. Swenor. 2023. “Food insecurity gaps in the supplemental nutrition assistance program based on disability status.” *Disability and Health Journal* 16(4):101486.

Sango, P.N., M. Bello, R. Deveau, K. Gager, B. Boateng, H.K. Ahmed, and M.N. Azam. 2022. “Exploring the role and lived experiences of people with disabilities working in the agricultural sector in northern Nigeria.” *African Journal of Disability* 16(11):897.

Saugeres, L. 2011. “(Un)accommodating disabilities: housing, marginalization and dependency in Australia.” *Journal of Housing and the Built Environment* 26(1):1–15.

Schmidt, P., and T.-F. Lin. 1984. “Simple tests of alternative specifications in stochastic frontier models.” *Journal of Econometrics* 24(3):349–361.

Stern, S. 1989. “Measuring the effect of disability on labor force participation.” *The Journal of Human Resources* 24(3):361–395.

Stuart, E.A. 2010. “Matching methods for causal inference: A review and a look forward.” *Statistical Science* 25(1):1–21.

Tiedemann, T., and U. Latacz-Lohmann. 2013. “Production risk and technical efficiency in organic and conventional agriculture - The case of arable farms in Germany.” *Journal of Agricultural Economics* 64(1):73–96.

Tom, T. 2024. “Zimbabwe’s fast-track land reform at 20: “Exploring disability inclusion and the attendant policy implications.” *Disability and Society* 39(3):594–619.

Trani, J.-F., P. Bakhshi, S. Myers Tlapek, D. Lopez, and F. Gall. 2015. “Disability and poverty in Morocco and Tunisia: A multidimensional approach.” *Journal of Human Development and Capabilities* 16(4):518–548.

Tripney, J., A. Roulstone, C. Vigurs, N. Hogrebe, and R. Stewart. 2017. “Interventions to improve the labour market situation of adults with physical and/or sensory disabilities in low- and middle-income countries: A systematic review.” *Campbell Systematic Reviews* 13(1):1–192.

Tsiboe, F. 2021. “Chronic sources of low cocoa production in Ghana: New insights from meta-analysis of old survey data.” *Agricultural and Resource Economics Review*:1–26.

Tsiboe, F. 2020. “Nationally representative farm/household level dataset on crop production in Ghana from 1987-2017.” *SSRN*. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4134518 [Accessed March 30, 2024].

Tsiboe, F., P. Aseete, and J.G. Djokoto. 2021. "Spatiotemporal comparison of dry beans and groundnut production technology and inefficiency in Ghana." *Review of Agricultural and Applied Economics* 24(1):76–87.

Tsiboe, F., J. Asravor, and E. Osei. 2019. "Vegetable production technical efficiency and technology gaps in Ghana." *African Journal of Agricultural and Resource Economics* 14(4).

Tsiboe, F., J. Asravor, V. Owusu, and A. Mensah-Bonsu. 2022. "Production technology, efficiency, and productivity of cereal farms: Prospects for enhancing farm performance in Ghana." *Agricultural and Resource Economics Review* 51(3):579-609.

Tsiboe, F., I.S. Egyir, and G. Anaman. 2021. "Effect of fertilizer subsidy on household level cereal production in Ghana." *Scientific African* 13:e00916.

United Nations. 2018. "Disability and development report: Realizing the Sustainable Development Goals by, for and with persons with disabilities." Available at: https://social.un.org/publications/UN-Flagship-Report-Disability-Final.pdf [Accessed March 30, 2024].

United Nations. 2006. "Convention on the rights of persons with disabilities." General Assembly Res, 61, 106. Available at: https://www.un.org/en/development/desa/population/migration/generalassembly/docs/globalcompact/A_RES_61_106.pdf [Accessed October 4, 2025].

United Nations Women (UN Women). 2019. "*Progress of the world's women 2019–2020: Families in a changing world.*" *New York: UN Women.* Available at: https://www.unwomen.org/sites/default/files/Headquarters/Attachments/Sections/Library/Publications/2019/Progress-of-the-worlds-women-2019-2020-en.pdf [Accessed November 3, 2025].

UN Women. 2024. "*The care agenda: A regional perspective for East and Southern Africa*." UN Women East and Southern Africa Regional Office. Available at: https://africa.unwomen.org/en/digital-library/publications/2024/01/the-care-agenda-a-regional-perspective-for-east-and-southern-africa [Accessed October 30, 2025].

World Bank. 2024. "An accessible future for persons with disabilities: What does it take." *World Bank*. Available at: https://www.worldbank.org/en/news/immersive-story/2022/02/15/an-accessible-future-for-persons-with-disabilities-what-does-it-take [Accessed March 30, 2024].

World Health Organization (WHO). 2011. "World report on disability." Geneva, Switzerland. Available at: http://www.who.int/disabilities/world_report/2011/en/ [Accessed October 4, 2025].

World Health Organization (WHO). 2023. "Disability and health: fact sheet." Geneva: World Health Organization. Retrieved from https://www.who.int/news-room/fact-sheets/detail/disability-and-health [Accessed October 4, 2025].

Tables and Figures

Table 1. Summary Statistics of Crop Producers in Ghana (2012-2017)

Variable	Mean (SD)			Trend (%) [a]		
	Pooled (n= 19,862)	Not disabled (n= 17,990)	Disabled (n= 1,872)	Pooled (n= 19,862)	Not disabled (n= 17,990)	Disabled (n= 1,872)
Farmer						
Female farmer (dummy)	0.25 (0.43)	0.91 (0.29)	0.09 (0.29)	-1.45** [0.68]	0.54*** [0.15] †	-5.21*** [1.42] †
Age (years)	47.33 (15.16)	46.88 (15.03)	51.67 (15.80)	0.63*** [0.13]	0.66*** [0.14] †	0.34 [0.44] †
Education (years)	4.49 (5.16)	4.58 (5.17)	3.69 (4.98)	2.66*** [0.51]	2.68*** [0.52] †	2.48 [2.09] †
Selected crop production (real GH₵/ha)						
All crops	1280.84 (1734.43)	1293.19 (1741.43) †	1162.17 (1661.40) †	11.67*** [0.61]	11.99*** [0.63] †	8.66*** [2.21] †
Maize	2531.11 (7238.73)	2575.22 (7415.95) †	2106.32 (5216.84) †	30.19*** [2.18]	31.54*** [2.34]	17.60*** [5.64]
Rice	1184.07 (2038.12)	1185.49 (2011.76) †	1172.39 (2246.54) †	12.81*** [1.91]	11.64*** [1.88] †	21.96*** [8.03] †
Millet	894.88 (1335.52)	895.62 (1308.23) †	889.16 (1530.36) †	1.48 [1.30]	1.81 [1.38] †	-1.05 [3.89] †
Sorghum	883.78 (1223.74)	895.87 (1223.56) †	787.68 (1223.27) †	0.67 [1.44]	1.48 [1.51] †	-5.92 [4.71] †
Beans	947.63 (1715.62)	951.73 (1679.98) †	914.05 (1986.05) †	8.99*** [1.63]	8.88*** [1.64] †	9.90 [6.59] †
Peanut	1239.47 (2502.86)	1236.52 (2473.55) †	1266.63 (2761.03) †	17.43*** [1.81]	17.31*** [1.85] †	18.51*** [7.07] †
Cassava	1361.29 (2781.28)	1351.48 (2745.72) †	1474.63 (3165.37) †	69.70*** [7.63]	70.52*** [8.14] †	60.65*** [19.21] †
Yam	1634.16 (2870.58)	1612.19 (2843.48) †	1919.36 (3201.42) †	287.46 [301.51]	299.64 [332.13] †	172.21 [277.81] †
Cocoyam	477.47 (1065.11)	492.52 (1089.97) †	244.78 (508.43) †	47.95* [25.19]	47.44* [27.50] †	41.22 [32.46] †
Plantain	1037.24 (2061.35)	1041.83 (2073.86) †	975.03 (1888.43) †	96.91*** [25.29]	100.91*** [27.58] †	52.37*** [19.81] †
Pepper	664.36 (1470.13)	680.84 (1500.29)	470.07 (1040.26)	12.00 [16.74]	4.55 [19.20]	37.60*** [11.79]
Okra	350.26 (658.73)	345.88 (638.68) †	389.98 (825.40) †	7.36* [4.27]	8.16* [4.50] †	0.25 [13.87] †
Tomato	526.99 (1280.09)	522.25 (1304.22) †	598.01 (863.44) †	6.74 [10.07]	6.96 [10.70] †	3.54 [16.71] †
Cocoa	650.12 (1593.15)	668.17 (1636.63) †	435.72 (908.55) †	35.00*** [4.23]	37.16*** [4.56]	10.70 [8.04]
Palm	1139.80 (3473.80)	1159.39 (3549.63) †	873.49 (2212.93) †	-17.57 [90.87]	-17.45 [92.13] †	-22.39 [557.88] †
Land (ha)	1.83 (2.41)	1.83 (2.41) †	1.77 (2.50) †	2.13*** [0.51]	1.80*** [0.52] †	5.22*** [1.91] †
Land owned (dummy)	0.62 (0.49)	0.62 (0.49) †	0.63 (0.48) †	3.68*** [0.32]	3.67*** [0.34] †	3.79*** [1.05] †
Crop diversification (index)	0.46 (0.26)	0.46 (0.26)	0.49 (0.25)	-3.51*** [0.24]	-3.51*** [0.25] †	-3.49*** [0.76] †
Seed (real GH₵/ha)	135.12 (684.10)	139.17 (709.58)	96.21 (353.76)	52.62*** [5.40]	55.42*** [5.96]	27.69*** [6.99]
Household labor (AE)	7.17 (6.69)	7.06 (6.56)	8.24 (7.74)	8.66*** [0.40]	8.42*** [0.42]	10.86*** [1.41]
Hired labor (man-days/ha)	20.03 (78.85)	20.11 (72.25) †	19.32 (125.74) †	5.44*** [1.56]	6.13*** [1.48] †	-1.14 [8.59] †
Fertilizer (Kg/ha)	263.20 (7154.01)	270.50 (7506.50) †	193.06 (1231.44) †	28.54* [14.77]	28.26* [16.28] †	31.11* [18.59] †
Pesticide (Liter/ha)	19.51 (295.07)	20.11 (309.57)	13.68 (53.02)	10.54 [6.71]	10.34 [7.38] †	12.40 [8.23] †
Mechanization (dummy)	0.05 (0.21)	0.04 (0.21)	0.08 (0.27)	-4.09** [2.05]	-3.22 [2.20] †	-12.48** [5.05] †
Irrigation (dummy)	0.02 (0.14)	0.02 (0.14) †	0.02 (0.15) †	-1.39 [3.27]	-1.24 [3.39] †	-2.84 [11.95] †
Credit (dummy)	0.12 (0.33)	0.12 (0.33) †	0.12 (0.32) †	-0.35 [1.18]	-0.94 [1.23] †	5.25 [4.17] †
Household						
Size (AE)	5.45 (3.17)	5.37 (3.14)	6.21 (3.38)	-0.74*** [0.27]	-0.73** [0.29] †	-0.84 [0.83] †
Dependency (ratio)	1.42 (1.70)	1.42 (1.70)	1.42 (1.65)	-1.78*** [0.52]	-2.29*** [0.54]	3.17* [1.85]

* Significance levels: * p<0.10, ** p<0.05, ***p<0.01. † Indicate insignificant (p<0.05) variation across disability status.

[a] The trend was estimated via a linear regression for continuous variables and a logit model for dummies. The mean mid-rate interbank FX rate between the Ghana cedi (GH₵) and the US Dollar ($) for December 2019 was 5.54 GH₵/$ as reported by the Bank of Ghana. *All monetary terms are in constant 2016/17 Ghana cedis.* Data Sources: Ghana Living Standards Survey [waves 6-7]. Standard deviations are in parenthesis and standard errors are in brackets.

Table 2: Disability Prevalence Among Ghanaian Crop Farmers (2012-2017)[3]

Crop	Type of disability							
	Any	**Physical**	**Sight**	**Hearing**	**Intellect**	**Speech**	**Emotional**	**Other**
	Headcount ratio over the periods 2012/13 and 2016/17							
Millet	0.116 (0.320)	0.029 (0.168)	0.027 (0.163)	0.014 (0.116)	0.005 (0.070)	0.010 (0.098)	0.004 (0.062)	0.034 (0.180)
Sorghum	0.112 (0.315)	0.037 (0.188)	0.027 (0.161)	0.015 (0.120)	0.004 (0.065)	0.010 (0.099)	0.004 (0.062)	0.023 (0.151)
Rice	0.109 (0.311)	0.030 (0.171)	0.023 (0.150)	0.009 (0.097)	0.005 (0.073)	0.007 (0.082)	0.004 (0.062)	0.034 (0.181)
Okra	0.099 (0.299)	0.020 (0.141)	0.012 (0.110)	0.012 (0.110)	-	0.016 (0.126)	-	0.037 (0.188)
Maize	0.094 (0.292)	0.027 (0.162)	0.018 (0.133)	0.011 (0.103)	0.006 (0.076)	0.008 (0.091)	0.003 (0.054)	0.025 (0.155)
Beans	0.109 (0.311)	0.033 (0.179)	0.024 (0.155)	0.011 (0.103)	0.006 (0.078)	0.012 (0.108)	0.003 (0.050)	0.025 (0.156)
Any crop	0.094 (0.292)	0.027 (0.163)	0.019 (0.137)	0.011 (0.105)	0.006 (0.077)	0.009 (0.092)	0.003 (0.054)	0.022 (0.148)
Peanut	0.098 (0.297)	0.029 (0.169)	0.024 (0.152)	0.011 (0.106)	0.006 (0.075)	0.009 (0.096)	0.002 (0.046)	0.019 (0.136)
Cocoa	0.078 (0.268)	0.026 (0.159)	0.015 (0.120)	0.009 (0.095)	0.005 (0.074)	0.005 (0.069)	0.003 (0.054)	0.016 (0.127)
Cassava	0.080 (0.271)	0.022 (0.148)	0.012 (0.109)	0.009 (0.093)	0.007 (0.081)	0.008 (0.087)	-	0.022 (0.145)
Banana	0.112 (0.317)	0.028 (0.166)	-	0.019 (0.136)	-	-	-	-
Plantain	0.069 (0.253)	0.022 (0.147)	0.010 (0.100)	0.006 (0.076)	0.007 (0.084)	0.006 (0.076)	-	0.016 (0.127)
Pepper	0.078 (0.269)	0.015 (0.123)	0.014 (0.118)	0.006 (0.077)	0.007 (0.084)	0.007 (0.084)	0.004 (0.060)	0.026 (0.159)
Yam	0.072 (0.258)	0.019 (0.136)	0.013 (0.112)	0.008 (0.092)	0.004 (0.065)	0.006 (0.078)	0.002 (0.043)	0.020 (0.140)
Cocoyam	0.061 (0.239)	0.022 (0.148)	0.016 (0.126)	-	-	0.006 (0.078)	-	0.006 (0.078)
Tomato	0.063 (0.243)	0.011 (0.105)	0.007 (0.086)	-	-	-	-	0.026 (0.159)
Eggplant	0.048 (0.214)	0.012 (0.109)	-	-	-	-	-	-
Palm	0.069 (0.253)	0.015 (0.121)	0.004 (0.061)	0.011 (0.105)	0.015 (0.121)	0.006 (0.074)	-	0.017 (0.128)
	Percentage change in headcount ratio from 2012/13 and 2016/17							
Banana	-5.055 [6.515]	-3.223 [3.640]	-	-0.842 [2.818]	-	-	-	-
Cocoyam	2.174 [2.125]	1.641 [1.289]	0.525 [1.125]	-	-	0.299 [0.687]	-	0.299 [0.687]
Plantain	-0.090 [1.059]	1.687 [0.630]	0.729 [0.401]	0.103 [0.312]	-0.668 [0.353]	-0.401 [0.319]	-	-1.779 [0.534]
Eggplant	4.605 [3.680]	0.525 [1.803]	-	-	-	-	-	-
Palm	-1.368 [2.247]	0.986 [0.993]	-0.136 [0.549]	0.357 [0.891]	-0.544 [1.091]	0.178 [0.632]	-	-2.524 [1.255]
Cassava	0.986 [0.818]	1.183 [0.448]	0.761 [0.330]	0.649 [0.285]	-0.300 [0.240]	0.262 [0.263]	-	-1.827 [0.438]
Okra	0.358 [2.879]	0.323 [1.283]	-0.623 [0.971]	1.010 [1.023]	-	2.708 [1.599]	-	-3.501 [1.626]
Yam	0.160 [1.292]	1.043 [0.693]	-0.078 [0.554]	0.439 [0.505]	-0.271 [0.310]	0.384 [0.398]	-0.081 [0.206]	-1.385 [0.666]
Cocoa	1.112 [1.093]	1.741 [0.606]	0.376 [0.471]	0.050 [0.390]	-0.660 [0.354]	0.052 [0.284]	0.273 [0.197]	-0.830 [0.562]
Maize	1.179 [0.585]	0.498 [0.319]	0.990 [0.262]	0.302 [0.204]	0.173 [0.149]	0.485 [0.177]	0.179 [0.102]	-1.602 [0.326]
Any crop	1.841 [0.532]	0.795 [0.287]	1.207 [0.246]	0.449 [0.191]	-0.053 [0.148]	0.436 [0.164]	0.214 [0.091]	-1.219 [0.281]
Pepper	0.908 [2.141]	0.323 [0.927]	-0.028 [0.860]	0.695 [0.656]	-0.544 [0.531]	1.046 [1.127]	0.523 [0.526]	-1.287 [1.065]
Peanut	2.999 [0.922]	0.873 [0.524]	1.613 [0.450]	0.699 [0.313]	0.571 [0.238]	0.629 [0.297]	0.166 [0.132]	-1.499 [0.451]
Beans	1.569 [1.139]	1.056 [0.631]	0.997 [0.541]	0.706 [0.363]	0.268 [0.270]	0.481 [0.429]	0.051 [0.179]	-1.943 [0.602]
Tomato	0.000 [2.988]	-0.357 [1.252]	0.268 [1.087]	-	-	-	-	0.179 [1.966]
Rice	1.507 [1.233]	0.675 [0.662]	0.738 [0.586]	0.085 [0.380]	0.764 [0.269]	0.248 [0.316]	0.190 [0.233]	-1.315 [0.750]
Millet	3.284 [1.194]	0.230 [0.631]	1.636 [0.600]	0.247 [0.432]	0.714 [0.234]	0.858 [0.348]	0.245 [0.223]	-0.829 [0.697]
Sorghum	3.230 [1.334]	2.194 [0.779]	1.236 [0.669]	0.534 [0.498]	0.177 [0.272]	1.302 [0.506]	-0.081 [0.257]	-2.036 [0.622]

[3] Headcount ratios by disability type are not mutually exclusive, as some farmers may experience more than one disability. However, the individual headcount ratios are small (ranging from about 0.2% to 3.7% across crops and disability types), which implies that the overlap is even smaller. As such, while some multiple-disability cases may exist, their influence on the reported estimates is unlikely to be material.

Standard deviations are in parenthesis and standard errors are in brackets.
Data Sources: Ghana Living Standards Survey [waves 6-7].

Table 3. Input Elasticities and Production Variability by Disability Status in Ghana (2012-2017)

	Naïve national frontier	Group frontier			Meta-frontier	
		Non-disabled [A]	Disabled [B]	Difference (%) $[(\boldsymbol{B}-\boldsymbol{A})]$	Matched	Unmatched
Elasticity						
Land	0.605*** (0.001)	0.608*** (0.001)	0.561*** (0.117)	-0.038 (0.117)	0.581*** (0.060)	0.605*** (0.011)
Planting material	0.049*** (0.000)	0.049*** (0.000)	0.052*** (0.002)	0.003 (0.002)	0.050*** (0.002)	0.049*** (0.000)
Household labor	0.197*** (0.001)	0.198*** (0.001)	0.221*** (0.049)	0.018 (0.049)	0.207*** (0.019)	0.200*** (0.001)
Hired labor	0.020*** (0.000)	0.020*** (0.000)	0.021 (0.016)	0.001 (0.016)	0.021*** (0.006)	0.020*** (0.001)
Fertilizer	0.026*** (0.000)	0.025*** (0.000)	0.026*** (0.009)	0.001 (0.009)	0.026*** (0.004)	0.025*** (0.000)
Pesticide	0.011*** (0.000)	0.011*** (0.000)	0.017*** (0.002)	0.006*** (0.002)	0.013*** (0.002)	0.011*** (0.000)
Returns to scale	0.908*** (0.001)	0.911*** (0.001)	0.899*** (0.137)	-0.009 (0.137)	0.898*** (0.064)	0.911*** (0.009)
Technology/efficiency						
Technology gap ratio (TGR)						
Matched	-	0.931*** (0.076)	0.818*** (0.012)	-0.113 (0.071)	-	-
Unmatched	-	0.971*** (0.008)	0.853*** (0.030)	-0.117*** (0.038)	-	-
Pure farmer technical efficiency (TE)						
Matched	0.775*** (0.001)	0.777*** (0.001)	0.780*** (0.051)	0.004 (0.051)	-	-
Unmatched	0.799*** (0.000)	0.800*** (0.000)	0.780*** (0.051)	-0.019 (0.051)	-	-
Meta-frontier technical efficiency (MTE)						
Matched	0.678*** (0.051)	0.725*** (0.057)	0.630*** (0.045)	-0.095*** (0.012)	-	-
Unmatched	0.766*** (0.008)	0.776*** (0.006)	0.657*** (0.025)	-0.119*** (0.019)	-	-
Model diagnostics						
Sample size	19862	17990	1872	-	3744	19862
Monotonicity satisfaction rate	49.10	37.38	23.08	-	99.95	99.99
Curvature satisfaction rate	21.96	21.98	21.58	-	29.54	21.97
Schmidt & Lin (1984) [a]	-0.024***	-0.038***	0.138***	-	-0.114***	-4.362***
Coelli, (1995) [a]	-1.366	-2.073**	2.436**	-	-2.850***	-250.996***
Gutierrez (2001) [a]	1356.755**	1261.549**	123.599**	-	973.879**	14333.240**
Log likelihood	-26821	-24321	-2453	-	3554	34159
No. of parameters	32	32	32	-	32	32
Meta frontier LR test	-	-	-	-	7202.335**	68412.738***
Ratio variance due to inefficiency	0.310*** (0.001)	0.317*** (0.001)	0.295*** (0.053)	-	0.993*** (0.086)	0.934*** (0.219)

Significance levels: * p<0.10, ** p<0.05, ***p<0.01

[a] Null hypothesis of no one-sided error (i.e., no inefficiency) was tested.

Meta Stochastic Frontier Analysis was jointly performed on Ghana Living Standards Survey [waves 6 and 7]).

Standard errors were estimated via the jackknife resampling method by iteratively generating 100 resampled datasets by randomly excluding one enumeration area from each survey for every resample. All values in parenthesis are standard deviations.

Table 4. Parity in Technology Level and Technical Efficiency Based on Member Disability

	Non-disabled [A]	Disabled [B]	Difference (%) $[(B-A)]$
Technology gap ratio (TGR)			
Anyone including farmer	0.931*** (0.076)	0.818*** (0.012)	-0.113 (0.071)
Farmer	0.862*** (0.012)	0.935*** (0.024)	0.072*** (0.025)
Spouse of farmer	0.957*** (0.001)	0.972*** (0.001)	0.015*** (0.001)
Child (adopted or biological) of farmer	0.897*** (0.021)	0.682*** (0.044)	-0.214*** (0.029)
Spouse or child of farmer	0.943*** (0.033)	0.783*** (0.013)	-0.160*** (0.020)
Household member other than spouse or child	0.744*** (0.005)	0.866*** (0.005)	0.122*** (0.003)
Pure farmer technical efficiency (TE)			
Anyone including farmer	0.777*** (0.001)	0.780*** (0.051)	0.004 (0.051)
Farmer	0.777*** (0.001)	0.527*** (0.062)	-0.250*** (0.062)
Spouse of farmer	0.777*** (0.001)	0.574*** (0.003)	-0.203*** (0.003)
Child (adopted or biological) of farmer	0.777*** (0.001)	0.920*** (0.045)	0.143*** (0.045)
Spouse or child of farmer	0.777*** (0.001)	0.795*** (0.004)	0.018*** (0.004)
Household member other than spouse or child	0.777*** (0.001)	0.635*** (0.001)	-0.141*** (0.001)
Meta-frontier technical efficiency (MTE)			
Anyone including farmer	0.725*** (0.057)	0.630*** (0.045)	-0.095*** (0.012)
Farmer	0.679*** (0.009)	0.495*** (0.038)	-0.184*** (0.045)
Spouse of farmer	0.748*** (0.001)	0.561*** (0.003)	-0.187*** (0.003)
Child (adopted or biological) of farmer	0.702*** (0.014)	0.618*** (0.016)	-0.084*** (0.007)
Spouse or child of farmer	0.733*** (0.025)	0.625*** (0.014)	-0.109*** (0.010)
Household member other than spouse or child	0.595*** (0.003)	0.537*** (0.003)	-0.058*** (0.001)

Significance levels: * p<0.10, ** p<0.05, ***p<0.01
Meta Stochastic Frontier Analysis was jointly performed on Ghana Living Standards Survey [waves 6 and 7]).
Standard errors were estimated via the jackknife resampling method by iteratively generating 100 resampled datasets by randomly excluding one enumeration area from each survey for every resample. All values in parenthesis are standard deviations.

Figure 1. Crop Production Input and Output Disability Gaps in Ghana

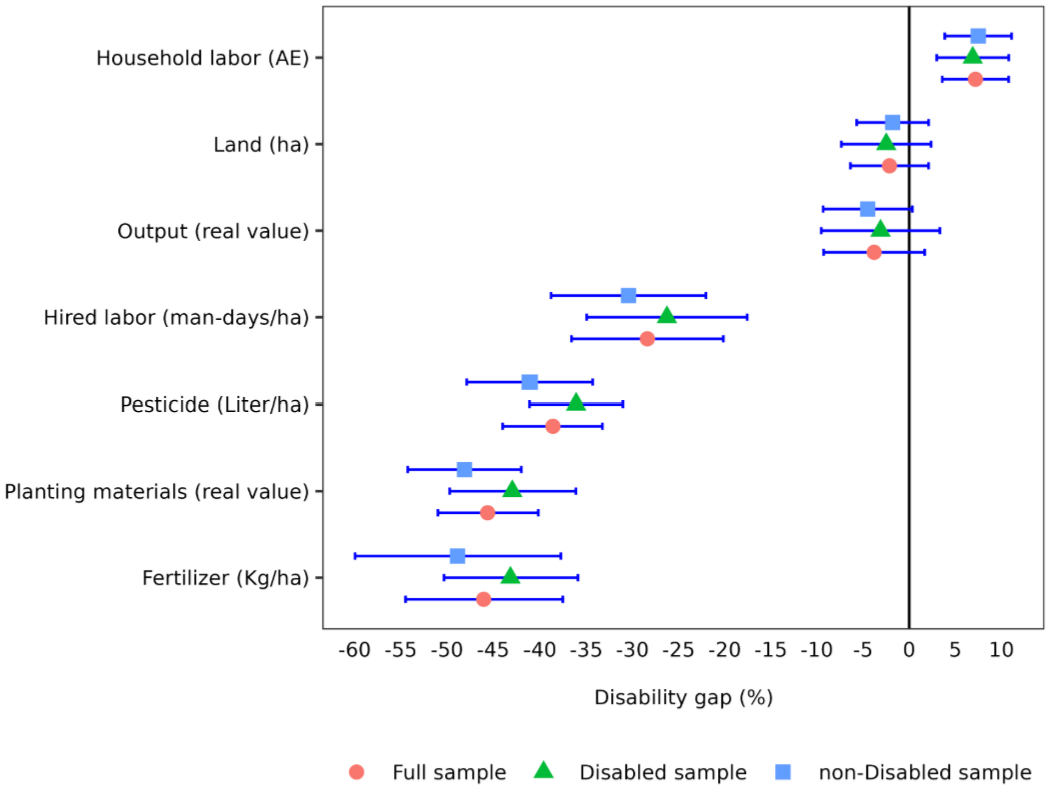


Figure 2. Disability Parity in Crop Production Technology Adoption and Technical Efficiency by Farmer Gender, Age, and Education in Ghana (2012-2017)

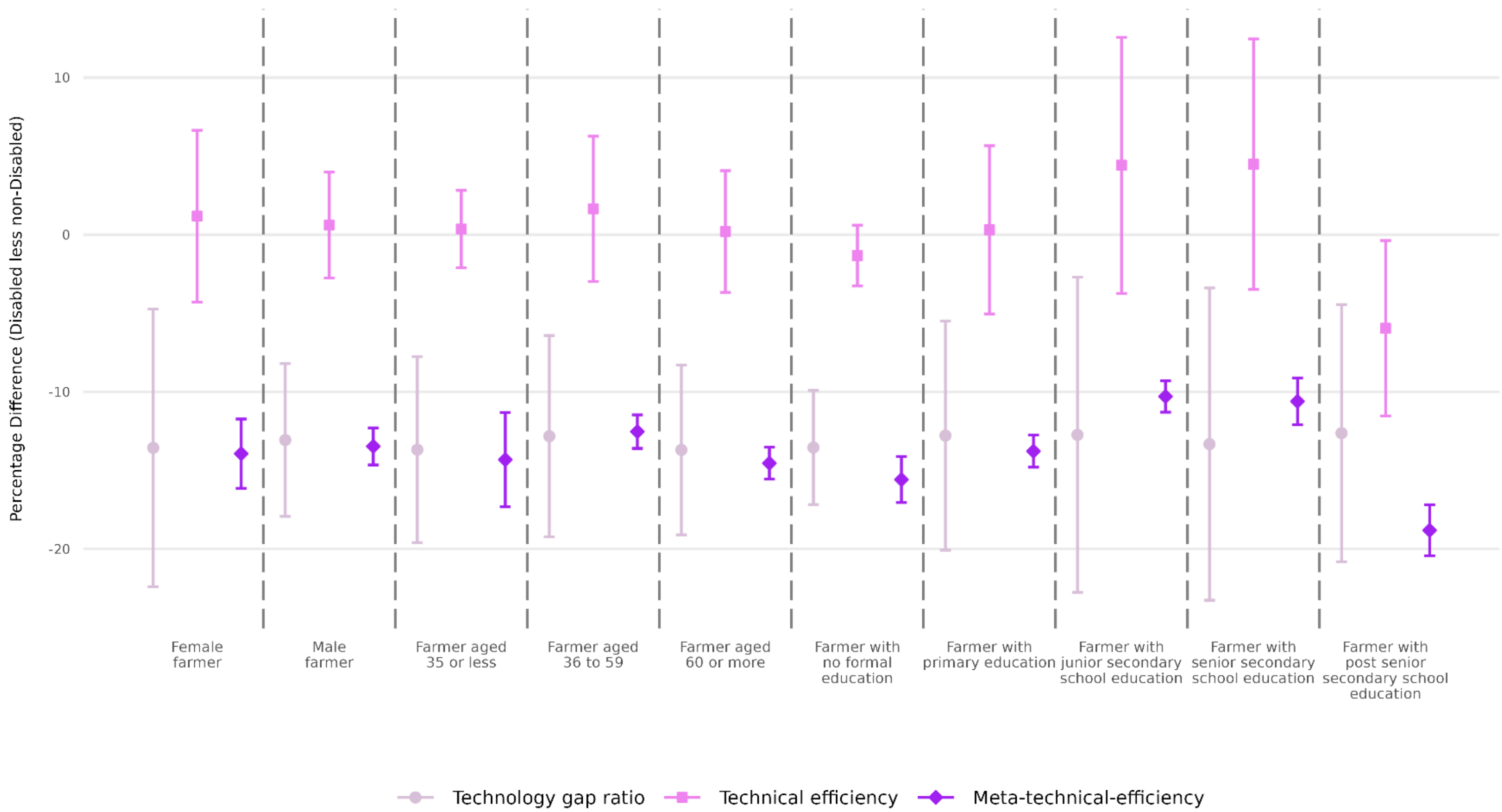
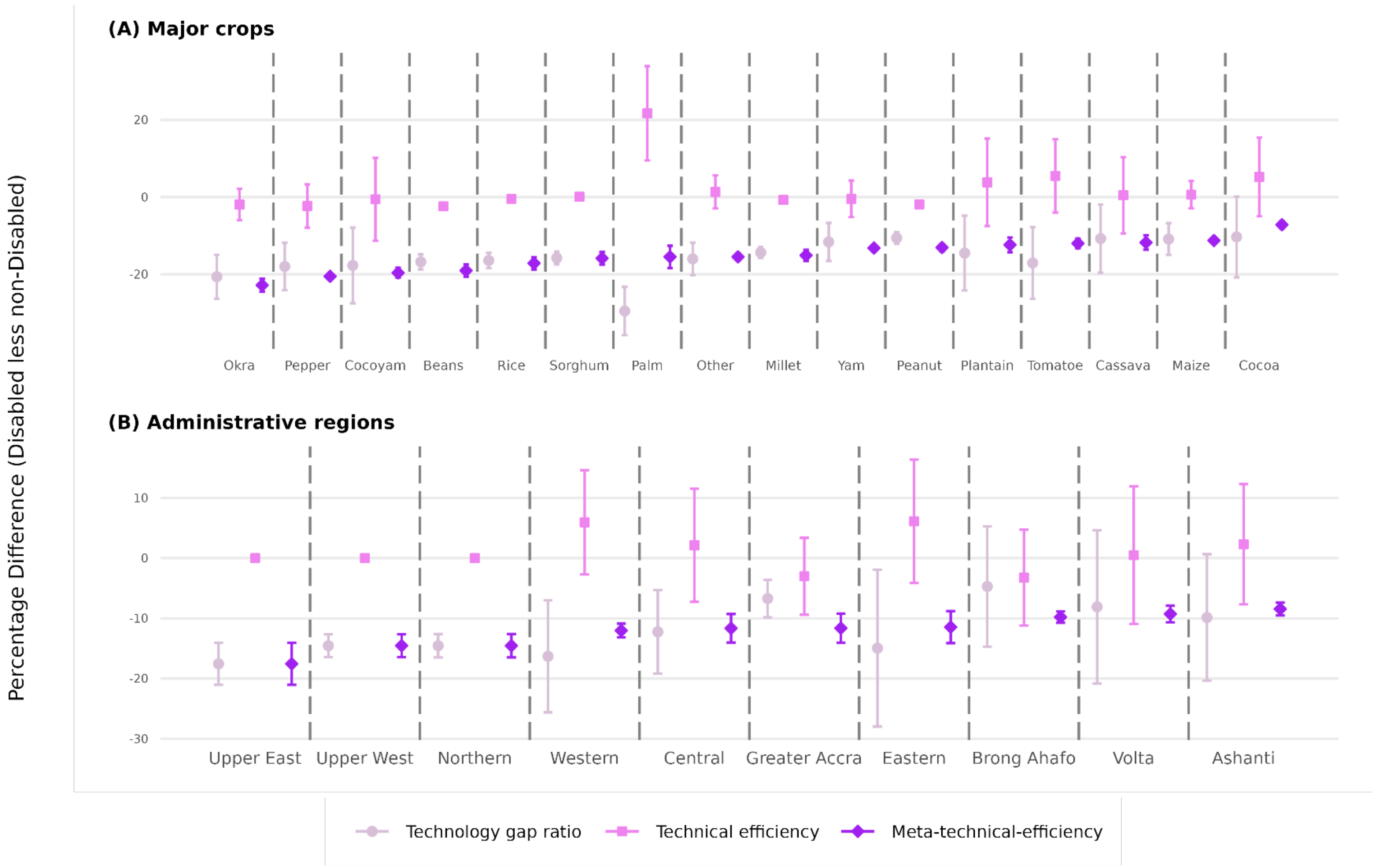


Figure 3. Disability Parity in Crop Production Technology Adoption and Technical Efficiency by Major Crops and Administrative Regions in Ghana (2012-2017)



Appendix

Note S1 Summary statistics of the sampled farmers

This section provides summary statistics of the key variables used in the model. Table 1 presents an overview of crop producers in Ghana, disaggregated by disability status. Approximately 25% of the sampled respondents are females, with an average age and years of education of 47 and 4 years respectively. The average household size per adult equivalent is 5.43, with a dependency ratio of 1.42. In terms of crop production, the average total real value of all crops in our sample is GH₵ 1,281. Significant variations are observed in the value of selected crops across different categories, including cereals, roots and tubers, legumes, vegetables, starches, and tree crops. Maize production has the highest crop value (GH₵ 2,531), while okra has the lowest value (GH₵ 350). On average, farmers cultivate 1.83 hectares of land, with about 62% of the sampled farm households owning their land. Crop diversification, measured at 0.46, indicates the diversity of crops grown by farmers. The average value of planting materials used per hectare is GH₵ 135. Household labor per adult equivalent unit stands at 7.17, while the average number of hired labor, fertilizer, and pesticide use per hectare are 20 man-days, 263 kg, and 20 liters, respectively. Only a small percentage of farm households have access to mechanization (5%), irrigation (2%), and credit (12%).

We observed significant differences between farmers with and without disabilities in several aspects, including the proportion of females, age, years of education, production, crop diversification, value of seeds, household labor per adult equivalent (AE), quantity of pesticide use, proportion of farmers using mechanization, and household size. Approximately 9% of the disabled farmers are females, compared to 91% of the non-disabled farmers. Disabled farmers are generally older and have fewer years of education, on average. Non-disabled farmers recorded significantly higher production of pepper, value of planting materials, and pesticide use than their disabled counterparts. However, disabled farmers tend to diversify their crop portfolios more and rely more on hired labor than non-disabled farmers. Additionally, a relatively higher proportion of disabled farmers use mechanization services and have larger household sizes relative to non-disabled farmers. The high level of crop diversification among disabled farmers may be attributed to their use of mechanization services. The results further highlight that the cultivation of selected crops (maize, rice, millet, sorghum, beans, peanuts, cassava, yam, cocoyam, plantain, okra, tomato, cocoa, and palm) do not differ significantly based on the disability status of the farmer. This suggests that disability may not necessarily create a productivity gap in terms of production output from cultivating these crops. However, this result is only indicative, as there are both observable and unobservable factors that may influence these outcomes. In the subsequent section, we employ more robust estimation methods to test this hypothesis comprehensively.

We further show the trend for the respective covariates for the pooled, disabled and non-disabled samples. The pooled sample results show a positive trend of disability in crop production, factor inputs, and institutional factors except for palm, mechanization, irrigation, and credit. Variation exists in the disability trend for crop production, factor inputs, and institutional factors based on the sub-sample (non-disabled and disabled) analysis. Additional details regarding the summary statistics specific to the construct of disability (i.e., disabled close relatives, disabled other members), as well as trends in the characteristics of disabled crop producers, are available in Tables S1 and S2 of the online appendix.

Note S2 Drivers of technical inefficiency

Table S5 outlines the underlying factors that drive farm households' movement towards or away from their respective technically efficient frontiers. We find that regardless of the disability status of the household, being a female, an aged farmer, having more years of education and engaging in crop diversity tend to drive farm households further away from their technically feasible frontiers (Asravor et al., 2024; Tsiboe et al., 2022). Our results further indicate that enhancing farm household's access to mechanization and extension advisory services have the tendency to drive such farm households towards their efficient frontiers, irrespective of their disability status (Tsiboe et al., 2022). We however find mixed evidence for landownership and access to credit for households with and without disability. Whereas access to credit tends to drive non-disabled households away from their efficient frontier, it drives disabled households towards their efficient frontier. Additionally, disabled farmers who owned farmlands tend to be technically less efficient. Consistent with Tsiboe et al. (2022) and Asravor et al. (2019), the agro-ecological zone of farm households determines their location with respect to their respective efficient frontiers. Whereas being in the Forest and Transitional zones tend to drive farmers away from their respective frontiers, those found in the Guinea and Sudan Savannah zones tend to move towards their respective efficient frontiers, regardless of their disability status.

Table S1. Disability variable construction

Question with {Preferred response}	*Number of choices allowed*	*Formulation*	
		GLSS 6	***GLSS 7***
Disability status indicator [takes on 1 if any of the conditions are met, 0 otherwise]			
What is/was the main reason why (NAME) has never attended school? {Disabled/ illness}	*Single*	*s2aq1a = 2*	*s2aq1a = 2*
Does (NAME) have any serious disability that limits his/her full participation in life activities (such as mobility, work, social life, etc.) {Yes}	*Single*	*s3aq26 = 1*	*s3aq26 = 1*
Why has (NAME) not made any effort to find work or start a business? [7 DAYS] {Disabled or unable to work (handicapped}	*Single*	*s4dq4 = 10*	*s4eq3 = 10*
Why was (NAME) not available for work during the last 7 days or within the next 4 weeks days? [7 DAYS] {Disabled}	*Single*	*s4dq10 = 5*	*s4eq10 = 5*
What was (NAME) doing when not available and not seeking for work? [12 MONTHS] {Disabled}	*Single*	*s4gq7 = 3*	-
Regarding the provision of public security services, have you ever been discriminated against because of your Disability {Disability}	*Single*	*s13cq27g = 1*	*s13cq28g = 1*
Was not allowed to participate in any community level activities because of Disability {Disability}	*Single*	*s13fq9 = 9*	*s13fq9 = 9*
Type of disability			
What type of disability does (NAME) have? Any combination of {Sight, Hearing, Speech, Physical, Intellectual, Emotional, Other (specify)}	*Multiple*	*s4gq7*	*s3aq27i*

Note: Disability indicators were constructed from the foundational GLSS6 and GLSS7 datasets and then integrated into the consolidated dataset using preserved household and member identifiers. An individual is classified as having a disability if they reported being unable to attend school, work, or seek employment due to disability or illness, indicated having a serious disability limiting daily activities, or reported discrimination/exclusion specifically because of a disability. The "type of disability" variable allows multiple responses (sight, hearing, speech, physical, intellectual, emotional, or other). Importantly, short-term illness or injury questions from Section 3a of the GLSS ("Health Condition in the Last 2 Weeks") were not used, ensuring that our definition reflects longer-term conditions. As the surveys do not distinguish congenital from acquired disabilities, our operational measure encompasses both.

Table S2. Summary Statistics of Crop Producers in Ghana (2012-2017)

Variable	Pooled (n=19862)	Disabled person: Farmer (n=625)	Spouse of farmer (n=313)	Child (adopted or biological) of farmer (n=554)	Spouse or child of farmer (n=854)	Household member other than spouse or child (n=1063)
Farmer						
Female farmer (dummy)	0.25 (0.43)	0.03 (0.18) †	0.02 (0.13) †	0.03 (0.17) †	0.05 (0.21) †	0.06 (0.23) †
Age (years)	47.33 (15.16)	54.55 (16.73)	53.74 (14.75)	53.34 (13.68)	52.29 (15.03)	51.55 (16.55)
Education (years)	4.49 (5.16)	3.41 (5.03)	3.48 (4.76)	3.53 (4.74)	3.65 (4.77)	3.71 (5.15)
Selected crop production (real GH₵/ha)						
All crops	1280.84 (1734.43)	1106.63 (1631.81) †	1083.67 (1682.33) †	1175.88 (1666.27) †	1116.40 (1591.49) †	1167.84 (1670.62) †
Maize	2531.11 (7238.73)	2027.21 (5830.71) †	1995.92 (4806.25) †	1978.00 (4308.30) †	2110.23 (4868.93) †	2024.52 (5299.89) †
Rice	1184.07 (2038.12)	863.84 (1267.28)	923.98 (1604.56)	1338.84 (2317.48)	1244.44 (2106.55)	1090.68 (2262.27)
Millet	894.88 (1335.52)	875.54 (1486.45) †	800.78 (1376.75) †	969.96 (1661.49) †	871.59 (1409.70) †	870.92 (1538.65) †
Sorghum	883.78 (1223.74)	805.87 (1083.82) †	459.29 (416.79) †	706.28 (814.43) †	538.27 (567.26) †	904.61 (1418.84) †
Beans	947.63 (1715.62)	929.79 (2430.77)	712.66 (998.85)	931.05 (2019.80)	876.20 (1755.24)	907.22 (2070.12)
Peanut	1239.47 (2502.86)	1621.41 (3820.05) †	1105.23 (1521.65) †	873.54 (1119.79) †	937.49 (1250.23) †	1434.49 (3307.86) †
Cassava	1361.29 (2781.28)	1521.39 (3343.04) †	1495.18 (3489.49) †	1327.39 (2614.49) †	1440.15 (3031.01) †	1483.50 (3235.28) †
Yam	1634.16 (2870.58)	2437.15 (4022.65) †	1005.33 (1192.69) †	1915.05 (3405.44) †	1701.27 (2939.46) †	2085.37 (3399.75) †
Cocoyam	477.47 (1065.11)	290.26 (531.42) †	144.39 (151.63) †	-	142.62 (122.94) †	312.88 (647.24) †
Plantain	1037.24 (2061.35)	954.59 (1575.75) †	406.53 (527.37) †	1283.08 (2481.28) †	983.92 (2130.88) †	945.97 (1626.71) †
Pepper	664.36 (1470.13)	529.07 (1547.48) †	197.71 (207.93) †	586.72 (899.27) †	459.70 (808.68) †	470.80 (1259.22) †
Okra	350.26 (658.73)	281.80 (656.94) †	747.68 (1737.12) †	404.80 (612.27) †	299.88 (548.64) †	458.27 (999.59) †
Tomato	526.99 (1280.09)	251.54 (209.50) †	222.53 (286.37) †	1279.28 (1181.99) †	1015.09 (1117.56) †	227.28 (263.91) †
Cocoa	650.12 (1593.15)	304.16 (296.64) †	484.25 (965.14) †	581.17 (1406.04) †	550.26 (1273.61) †	329.13 (322.83) †
Palm	1139.80 (3473.80)	683.37 (1635.37) †	232.21 (366.57) †	1113.04 (2919.03) †	1093.38 (2724.20) †	518.75 (1097.67) †
Land (ha)	1.83 (2.41)	1.47 (1.82)	1.93 (2.76)	2.02 (2.79)	1.95 (2.74)	1.62 (2.27)
Land owned (dummy)	0.62 (0.49)	0.64 (0.48) †	0.63 (0.48) †	0.63 (0.48) †	0.62 (0.48) †	0.64 (0.48) †
Crop diversification (index)	0.46 (0.26)	0.46 (0.26) †	0.49 (0.25) †	0.49 (0.26) †	0.50 (0.26) †	0.49 (0.25) †
Seed (GHC/ha)	135.12 (684.10)	79.76 (253.70)	94.64 (458.64)	105.24 (333.03)	97.18 (369.78)	92.48 (327.66)
Household labor (AE)	7.17 (6.69)	6.37 (5.96) †	7.69 (6.70) †	9.17 (8.44) †	8.52 (7.92) †	8.14 (7.62) †
Hired labor (man-days/ha)	20.03 (78.85)	14.89 (52.91) †	30.93 (285.90) †	19.42 (55.32) †	23.21 (175.09) †	15.51 (53.56) †
Fertilizer (Kg/ha)	263.20 (7154.01)	132.89 (311.14) †	149.62 (358.66) †	305.08 (2194.90) †	249.41 (1769.26) †	143.81 (351.25) †
Pesticide (Liter/ha)	19.51 (295.07)	10.74 (27.77)	10.14 (21.86)	20.79 (88.14)	16.95 (71.74)	10.55 (27.39)
Mechanization (dummy)	0.05 (0.21)	0.08 (0.27)	0.07 (0.26)	0.08 (0.27)	0.07 (0.26)	0.08 (0.27)
Irrigation (dummy)	0.02 (0.14)	0.01 (0.08) †	0.01 (0.08) †	0.04 (0.20) †	0.03 (0.18) †	0.01 (0.11) †
Credit (dummy)	0.12 (0.33)	0.09 (0.29)	0.11 (0.31)	0.13 (0.33)	0.13 (0.33)	0.10 (0.30)
Household						
Size (AE)	5.45 (3.17)	4.88 (2.83)	5.74 (2.99)	7.20 (3.30)	6.85 (3.43)	5.73 (3.26)
Dependency (ratio)	1.42 (1.70)	1.25 (1.68)	1.55 (1.84)	1.48 (1.70)	1.51 (1.76)	1.37 (1.55)

* Significance levels: * p<0.10, ** p<0.05, ***p<0.01. † Indicate insignificant (p<0.05) variation across disability status.
The mean mid-rate interbank FX rate between the Ghana cedi (GH₵) and the US Dollar ($) for December 2019 was 5.54 GH₵/$ as reported by the Bank of Ghana
Data Sources: Ghana Living Standards Survey [waves 6-7]. All values in parenthesis are standard deviations.

Table S3. Trends in the Characteristics of Crop Producers in Ghana (2012-2017)

Variable	Pooled (n=19862)	Disabled person: Farmer (n=625)	Disabled person: Spouse of farmer (n=313)	Disabled person: Child (adopted or biological) of farmer (n=554)	Disabled person: Spouse or child of farmer (n=854)	Disabled person: Household member other than spouse or child (n=1063)
Farmer						
Female farmer (dummy)	-5.21*** [1.42] †	-6.94*** [2.34] †	-8.67** [3.57] †	-4.84* [2.63] †	-9.02*** [2.24] †	-3.40* [1.85] †
Age (years)	0.34 [0.44] †	0.11 [0.73] †	0.60 [0.89] †	0.31 [0.69] †	0.87 [0.59] †	-0.15 [0.61] †
Education (years)	2.48 [2.09] †	2.46 [3.91] †	0.38 [4.86] †	4.58 [3.72] †	4.45 [2.88] †	0.83 [2.87] †
Selected crop production (real GH₵/ha)						
All crops	8.66*** [2.21] †	9.14** [4.44] †	9.15* [4.97] †	12.51*** [4.04] †	11.26*** [3.20] †	5.95** [2.92] †
Maize	17.60*** [5.64]	15.84 [10.90] †	15.12 [12.91] †	21.83** [8.83] †	19.64** [8.01] †	14.64** [7.37] †
Rice	21.96*** [8.03] †	19.61** [9.31] †	38.04 [25.32] †	23.91* [12.94] †	22.53** [10.79] †	20.32* [10.86] †
Millet	-1.05 [3.89] †	13.05 [8.44] †	-5.42 [8.55] †	-1.08 [6.67] †	-0.08 [5.23] †	0.13 [5.23] †
Sorghum	-5.92 [4.71] †	-1.19 [8.33] †	-3.41 [6.84] †	1.19 [6.48] †	0.12 [4.92] †	-6.51 [5.94] †
Beans	9.90 [6.59] †	34.23 [24.12] †	-5.75 [8.38] †	21.05** [10.70] †	10.50 [7.22] †	10.66 [10.13] †
Peanut	18.51*** [7.07] †	31.11* [16.70] †	-2.80 [11.60] †	12.51* [6.99] †	6.35 [5.79] †	24.11** [10.12] †
Cassava	60.65*** [19.21] †	86.37 [87.86] †	-281.42 [4381.28] †	51.29** [25.59] †	93.15 [90.01] †	47.89*** [15.36] †
Yam	172.21 [277.81] †	-12.10 [67.94] †	13.79 [14.07] †	881.97 [15259.29] †	62.55** [31.21] †	-73.01 [269.02] †
Cocoyam	41.22 [32.46] †	26.40 [34.00] †	-60.35 [73.07] †	-	-72.92 [126.41] †	31.46 [290.43] †
Plantain	52.37*** [19.81] †	36.62** [15.97] †	-2.30 [7.34] †	-317.39 [6589.83] †	122.21 [237.36] †	32.40** [13.57] †
Pepper	37.60*** [11.79]	37.28*** [13.99] †	19.09 [18.16] †	57.98 [54.64] †	52.31* [26.85] †	25.44** [11.54] †
Okra	0.25 [13.87] †	-13.45 [20.48] †	538.76 [438.32] †	-22.09 [21.62] †	-3.97 [16.33] †	0.91 [19.73] †
Tomato	3.54 [16.71] †	-5.04 [10.85] †	-26.84*** [0.00] †	-18.88 [14.03] †	-7.81 [18.43] †	5.83 [12.81] †
Cocoa	10.70 [8.04]	-0.26 [6.60]	25.70 [24.24]	14.10 [15.92]	18.05 [13.83]	3.34 [5.10]
Palm	-22.39 [557.88] †	293.16 [527.78] †	-32.74 [27.47] †	24.74 [212.32] †	51.51 [107.16] †	26.94 [29.60] †
Land (ha)	5.22*** [1.91] †	5.22* [2.70] †	4.01 [4.19] †	4.62 [3.40] †	5.16* [2.71] †	5.62** [2.51] †
Land owned (dummy)	3.79*** [1.05] †	1.50 [1.70] †	5.69** [2.51] †	3.75* [1.95] †	3.73** [1.60] †	3.71*** [1.30] †
Crop diversification (index)	-3.49*** [0.76] †	-4.94*** [1.42] †	-3.18* [1.75] †	-4.37*** [1.41] †	-4.43*** [1.16] †	-2.77*** [0.97] †
Seed (GHC/ha)	27.69*** [6.99]	9.00 [8.56]	87.18 [100.10]	46.53** [18.22]	48.98*** [17.78]	14.26** [6.46]
Household labor (AE)	10.86*** [1.41]	9.68*** [2.12] †	7.15** [2.97] †	10.92*** [2.55] †	10.75*** [2.13] †	10.47*** [1.76] †
Hired labor (man-days/ha)	-1.14 [8.59] †	5.65 [7.33] †	-33.10 [60.42] †	16.71* [8.55] †	0.15 [14.61] †	-1.04 [5.18] †
Fertilizer (Kg/ha)	31.11* [18.59] †	3.19 [5.18] †	26.38** [11.35] †	132.35 [447.15] †	75.90 [88.72] †	5.95 [4.14] †
Pesticide (Liter/ha)	12.40 [8.23] †	10.59* [5.93] †	15.44* [8.80] †	19.52 [18.52] †	21.78 [15.49] †	3.37 [4.16] †
Mechanization (dummy)	-12.48** [5.05] †	-15.31* [8.35] †	-25.14** [11.00] †	-9.19 [8.90] †	-12.56 [7.76] †	-12.28* [6.48] †
Irrigation (dummy)	-2.84 [11.95] †	-9.07 [23.00] †	1181.96*** [68.95] †	-14.03 [18.92] †	-0.09 [15.34] †	-2.91 [16.50] †
Credit (dummy)	5.25 [4.17] †	17.52** [7.12]	5.16 [9.75]	13.09* [6.70]	7.90 [5.54]	3.45 [6.06]
Household						
Size (AE)	-0.84 [0.83] †	0.55 [1.43] †	-0.36 [1.66] †	-1.42 [1.18] †	-0.74 [1.13] †	-0.55 [1.11] †
Dependency (ratio)	3.17* [1.85]	2.47 [4.05] †	4.38 [4.38] †	3.62 [3.00] †	3.68 [2.64] †	1.74 [2.46] †

* Significance levels: * p<0.10, ** p<0.05, ***p<0.01. † Indicate insignificant (p<0.05) variation across disability status.
The mean mid-rate interbank FX rate between the Ghana cedi (GH₵) and the US Dollar ($) for December 2019 was 5.54 GH₵/$ as reported by the Bank of Ghana
Data Sources: Ghana Living Standards Survey [waves 6-7]. All values in brackets are standard errors.

Table S4. Meta Stochastic Frontier Analysis Results for Ghanaian Crop Producers for the periods 2012/13 and 2016/17

	Naïve national frontier	Group frontier		Meta-frontier	
		Not disabled	Disabled	Matched	Unmatched
Production function					
Land [lnI1]	0.693*** (0.001)	0.696*** (0.001)	0.680*** (0.149)	0.680*** (0.088)	0.694*** (0.012)
Planting material [lnI2]	0.059*** (0.000)	0.059*** (0.000)	0.064*** (0.002)	0.059*** (0.002)	0.059*** (0.000)
Family labor [lnI3]	0.168*** (0.001)	0.169*** (0.000)	0.119*** (0.038)	0.172*** (0.023)	0.169*** (0.004)
Hired labor [lnI4]	0.027*** (0.000)	0.027*** (0.000)	0.028 (0.020)	0.028*** (0.008)	0.027*** (0.001)
Fertilizer [lnI5]	0.029*** (0.000)	0.028*** (0.000)	0.030*** (0.009)	0.029*** (0.004)	0.028*** (0.000)
Pesticide [lnI6]	0.019*** (0.000)	0.018*** (0.000)	0.031*** (0.003)	0.020*** (0.004)	0.019*** (0.000)
1/2 * lnI1 * lnI1	0.107*** (0.001)	0.108*** (0.001)	0.094*** (0.018)	0.108*** (0.005)	0.107*** (0.001)
lnI1*lnI2	0.000 (0.000)	0.000 (0.000)	0.000 (0.002)	0.000 (0.001)	0.000 (0.000)
lnI1*lnI3	-0.058*** (0.000)	-0.058*** (0.000)	-0.065*** (0.015)	-0.059*** (0.014)	-0.058*** (0.000)
lnI1*lnI4	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)	0.000 (0.000)
lnI1*lnI6	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)	0.000 (0.000)
lnI1*lnI5	0.000 (0.000)	0.000** (0.000)	0.000 (0.000)	-0.001** (0.000)	0.000 (0.000)
1/2 * lnI2 * lnI2	0.005*** (0.000)	0.005*** (0.000)	0.006*** (0.000)	0.005*** (0.000)	0.005*** (0.000)
lnI2*lnI3	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)
lnI2*lnI4	0.000 (0.000)	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lnI2*lnI6	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lnI2*lnI5	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)
1/2 * lnI3 * lnI3	0.019*** (0.000)	0.019*** (0.000)	0.057*** (0.007)	0.020*** (0.002)	0.020*** (0.002)
lnI3*lnI4	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000 (0.001)	0.000 (0.000)
lnI3*lnI6	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)
lnI3*lnI5	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)	0.000 (0.000)
1/2 * lnI4 * lnI4	0.002*** (0.000)	0.002*** (0.000)	0.002 (0.002)	0.002*** (0.000)	0.002*** (0.000)
lnI4*lnI6	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)
lnI4*lnI5	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
1/2 * lnI5 * lnI5	0.002*** (0.000)	0.002*** (0.000)	0.003*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
lnI5*lnI6	0.000 (0.000)	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
1/2 * lnI6 * lnI6	0.003*** (0.000)	0.002*** (0.000)	0.003*** (0.001)	0.002*** (0.000)	0.002*** (0.000)
Proportion of area under listed crop (base=maize)					
Cassava	-0.649*** (0.003)	-0.656*** (0.003)	-0.587*** (0.084)	-0.638*** (0.056)	-0.652*** (0.009)
Peanut	0.226*** (0.002)	0.212*** (0.002)	0.325*** (0.026)	0.232*** (0.027)	0.221*** (0.003)
Plantain	-0.489*** (0.004)	-0.493*** (0.003)	-0.436*** (0.116)	-0.471*** (0.066)	-0.491*** (0.007)
Rice	-0.052*** (0.002)	-0.039*** (0.002)	-0.154*** (0.046)	-0.051 (0.043)	-0.041*** (0.006)
Millet	-0.189*** (0.003)	-0.194*** (0.004)	-0.174 (0.114)	-0.174*** (0.053)	-0.190*** (0.010)
Sorghum	-0.272*** (0.003)	-0.265*** (0.003)	-0.303*** (0.082)	-0.260*** (0.021)	-0.265*** (0.005)
Beans	-0.206*** (0.003)	-0.191*** (0.003)	-0.338*** (0.015)	-0.196*** (0.025)	-0.193*** (0.003)
Yam	-0.084*** (0.003)	-0.083*** (0.003)	-0.111*** (0.041)	-0.082*** (0.009)	-0.084*** (0.005)
Cocoa	1.236*** (0.002)	1.232*** (0.002)	1.305*** (0.148)	1.251*** (0.093)	1.235*** (0.012)
Other	-0.400*** (0.004)	-0.359*** (0.004)	-0.740*** (0.065)	-0.368*** (0.038)	-0.369*** (0.008)
Ecological zone [base = Coastal Savanna]					
Forest	0.132*** (0.003)	0.143*** (0.003)	-0.014 (0.088)	0.108** (0.046)	0.143*** (0.004)
Guinea Savanah	-0.494*** (0.004)	-0.485*** (0.004)	-0.642*** (0.062)	-0.523*** (0.014)	-0.492*** (0.013)
Sudan Savanah	-0.506*** (0.003)	-0.485*** (0.003)	-0.694*** (0.016)	-0.529*** (0.026)	-0.489*** (0.016)
Transitional	0.017*** (0.003)	0.010*** (0.003)	0.070 (0.071)	0.107** (0.048)	0.015*** (0.003)
Period (base=2012/13)					
2016/17	0.056*** (0.002)	0.057*** (0.002)	-0.034 (0.104)	0.057* (0.033)	0.058*** (0.005)
Intercept	6.508*** (0.003)	6.509*** (0.003)	6.566*** (0.058)	6.594*** (0.117)	6.540*** (0.012)
Production risk function					
Intercept	-0.259*** (0.001)	-0.259*** (0.001)	-0.327*** (0.033)	-8.399*** (1.791)	-7.855*** (1.454)

Significance levels: * p<0.10, ** p<0.05, ***p<0.01

Meta Stochastic Frontier Analysis was jointly performed on Ghana Living Standards Survey [waves 6 and 7]).

Standard errors were estimated via the jackknife resampling method by iteratively generating 100 resampled datasets by randomly excluding one enumeration area from each survey for every resample. All values in parenthesis are standard deviations.

Table S5. Determinants Of Crop Production Technical Inefficiency and Disability Driven Technology Gaps in Ghana (2012-2017)

	Naïve national frontier	Group frontier		Meta-frontier	
		Not disabled	Disabled	Matched	Unmatched
Female farmer (dummy)	0.353*** (0.002)	0.374*** (0.002)	0.182 (0.127)	0.039 (0.033)	0.275* (0.139)
Age (years)	0.261*** (0.003)	0.261*** (0.004)	0.293*** (0.021)	0.262** (0.105)	0.608*** (0.017)
Education (years)	0.006*** (0.000)	0.008*** (0.000)	-0.001 (0.007)	0.001 (0.004)	-0.003 (0.004)
Land owned (dummy)	0.029*** (0.003)	0.024*** (0.003)	0.122*** (0.029)	-0.193** (0.077)	-0.157*** (0.055)
Crop diversification (index)	0.425*** (0.006)	0.452*** (0.006)	0.237*** (0.023)	0.594*** (0.163)	0.704*** (0.070)
Mechanization (dummy)	-0.989*** (0.031)	-0.995*** (0.030)	-4.329 (9.563)	0.161** (0.070)	0.178*** (0.018)
Credit (dummy)	0.125*** (0.003)	0.150*** (0.003)	-0.163*** (0.028)	-0.082*** (0.008)	-0.099 (0.061)
Extension (dummy)	0.013*** (0.003)	0.006** (0.003)	0.133 (0.145)	-0.128*** (0.025)	-0.174*** (0.036)
Ecological zone [base = Coastal Savanna]					
Forest	0.290*** (0.007)	0.298*** (0.007)	0.039 (0.283)	0.654*** (0.207)	0.765*** (0.242)
Guinea Savanah	-42.778*** (4.911)	-51.873*** (6.957)	-80.914*** (18.755)	0.286* (0.150)	0.248 (0.339)
Sudan Savanah	-44.093*** (4.499)	-58.410*** (7.943)	-88.772*** (24.231)	0.515 (3.474)	0.955*** (0.339)
Transitional	0.054*** (0.007)	-0.002 (0.007)	0.413* (0.221)	0.679*** (0.195)	-0.393** (0.166)
Period (base=2012/13)					
2016/17	-46.020*** (1.345)	-46.038*** (0.344)	-30.273*** (11.502)	0.686*** (0.226)	0.545 (0.466)
Intercept	-1.495*** (0.015)	-1.480*** (0.016)	-1.612*** (0.075)	-5.360*** (1.120)	-8.675*** (0.125)

Significance levels: * p<0.10, ** p<0.05, ***p<0.01

[a] Null hypothesis of no one-sided error (i.e., no inefficiency) was tested.

Meta Stochastic Frontier Analysis was jointly performed on Ghana Living Standards Survey [waves 6 and 7]. Standard errors were estimated via the jackknife resampling method by iteratively generating 100 resampled datasets by randomly excluding one enumeration area from each survey for every resample. All values in parenthesis are standard deviations.

Table S6: Covariate balancing

	Unmatched			Complementary Log-Log [PS]		
	Absolute Standardized Mean Differences	Variance Ratios	Kolmogorov-Smirnov (KS) Statistics	Absolute Standardized Mean Differences	Variance Ratios	Kolmogorov-Smirnov (KS) Statistics
Mean score across all listed variables	*0.042*	*1.224*	*0.029*	*0.028*	*1.242*	*0.018*
Farmer						
Female farmer (dummy)	*0.054*	-	*0.054*	*0.005*	-	*0.005*
Age (years)	*0.290*	*1.039*	*0.134*	*0.303*	*1.031*	*0.139*
Education (years)	*0.176*	*1.034*	*0.104*	*0.077*	*1.079*	*0.077*
Headship within household						
Member	*0.040*	-	*0.040*	*0.010*	-	*0.010*
Spouse of Head	*0.036*	-	*0.036*	*0.024*	-	*0.024*
Head	*0.076*	-	*0.076*	*0.034*	-	*0.034*
Marital status						
None	*0.005*	-	*0.005*	*0.017*	-	*0.017*
Married/Union	*0.032*	-	*0.032*	*0.026*	-	*0.026*
Divorced/Separated/Widowed	*0.037*	-	*0.037*	*0.009*	-	*0.009*
Ethnicity						
Akan	*0.052*	-	*0.052*	*0.016*	-	*0.016*
Ewe	*0.023*	-	*0.023*	*0.014*	-	*0.014*
Ga-Dangme	*0.001*	-	*0.001*	*0.001*	-	*0.001*
Guan	*0.001*	-	*0.001*	*0.010*	-	*0.010*
Gurma	*0.023*	-	*0.023*	*0.002*	-	*0.002*
Gursi	*0.001*	-	*0.001*	*0.002*	-	*0.002*
Mande	*0.005*	-	*0.005*	*0.006*	-	*0.006*
Mole-Dagbani	*0.003*	-	*0.003*	*0.006*	-	*0.006*
Non-Ghana	*0.001*	-	*0.001*	*0.005*	-	*0.005*
Other	*0.001*	-	*0.001*	*0.006*	-	*0.006*
Religion						
None	*0.021*	-	*0.021*	*0.040*	-	*0.040*
Christian	*0.004*	-	*0.004*	*0.026*	-	*0.026*
Islam	*0.006*	-	*0.006*	*0.022*	-	*0.022*
Traditional	*0.025*	-	*0.025*	*0.009*	-	*0.009*
Other	*0.002*	-	*0.002*	*0.000*	-	*0.000*
Crop production area share						
Maize	*0.056*	*1.052*	*0.032*	*0.004*	*1.026*	*0.021*
Rice	*0.057*	*1.338*	*0.016*	*0.002*	*1.093*	*0.009*
Millet	*0.056*	*1.218*	*0.023*	*0.049*	*1.221*	*0.015*
Sorghum	*0.080*	*1.636*	*0.022*	*0.035*	*1.263*	*0.010*
Beans	*0.046*	*1.252*	*0.020*	*0.032*	*1.303*	*0.009*
Peanut	*0.014*	*1.059*	*0.008*	*0.002*	*1.066*	*0.012*
Cassava	*0.018*	*1.017*	*0.023*	*0.055*	*1.120*	*0.034*
Yam	*0.063*	*1.305*	*0.020*	*0.012*	*1.116*	*0.008*
Cocoyam	*0.022*	*1.941*	*0.014*	*0.045*	*2.194*	*0.009*
Plantain	*0.136*	*1.576*	*0.050*	*0.058*	*1.407*	*0.017*
Pepper	*0.024*	*1.099*	*0.021*	*0.019*	*1.067*	*0.014*
Okra	*0.005*	*1.017*	*0.005*	*0.029*	*1.457*	*0.006*
Tomato	*0.016*	*1.058*	*0.009*	*0.039*	*1.543*	*0.008*
Cocoa	*0.056*	*1.096*	*0.030*	*0.032*	*1.070*	*0.019*
Palm	*0.062*	*1.455*	*0.013*	*0.061*	*1.403*	*0.011*
Land owned (dummy)	*0.030*	-	*0.030*	*0.035*	-	*0.035*
Crop diversification (index)	*0.127*	*1.022*	*0.069*	*0.105*	*1.023*	*0.056*
Credit (dummy)	*0.002*	-	*0.002*	*0.005*	-	*0.005*
Household						
Size (AE)	*0.293*	*1.227*	*0.144*	*0.248*	*1.099*	*0.129*
Dependency (ratio)	*0.017*	*1.087*	*0.061*	*0.067*	*1.234*	*0.057*
Dependency (ratio)	*0.067*	*1.186*	*0.054*	*0.055*	*1.265*	*0.069*
GLSS7 survey dummy	*0.084*	-	*0.084*	*0.006*	-	*0.006*
Urban locality	*0.024*	-	*0.024*	*0.003*	-	*0.003*
Region						
Ashanti	*0.031*	-	*0.031*	*0.003*	-	*0.003*
Brong Ahafo	*0.025*	-	*0.025*	*0.005*	-	*0.005*
Central	*0.000*	-	*0.000*	*0.003*	-	*0.003*
Eastern	*0.002*	-	*0.002*	*0.006*	-	*0.006*
Greater Accra	*0.003*	-	*0.003*	*0.001*	-	*0.001*
Northern	*0.007*	-	*0.007*	*0.003*	-	*0.003*
Upper East	*0.042*	-	*0.042*	*0.006*	-	*0.006*

Upper West	*0.004*	-	*0.004*	*0.001*	-	*0.001*
Volta	*0.048*	-	*0.048*	*0.006*	-	*0.006*
Western	*0.030*	-	*0.030*	*0.004*	-	*0.004*
Ecological zone						
Coastal Savanna	*0.008*	-	*0.008*	*0.002*	-	*0.002*
Forest Zone	*0.044*	-	*0.044*	*0.001*	-	*0.001*
Guinea Savanah	*0.021*	-	*0.021*	*0.004*	-	*0.004*
Sudan Savanah	*0.050*	-	*0.050*	*0.007*	-	*0.007*
Transitional Zone	*0.007*	-	*0.007*	*0.005*	-	*0.005*

Table S7: Covariate balance summary

Scaling matrix	***Mean standardized differences [A]***	***Mean variance ratio [B]***	***Kolmogorov-Smirnov (KS) Statistics [C]***	***Selection criteria $[((A-0)^2+(B-1)^2+(C-0)^2)/3]$***
Complementary Log-Log [PS]	*0.0275*	*1.2222*	*0.0178*	*0.0422*
Probit [PS]	*0.0227*	*1.2308*	*0.0154*	*0.0673*
Euclidean	*0.0206*	*1.3390*	*0.0167*	*0.0976*
Scaled Euclidean	*0.0201*	*1.3358*	*0.0161*	*0.1259*
Mahalanobis	*0.0214*	*1.3402*	*0.0165*	*0.1311*
Cauchit [PS]	*0.0230*	*1.3949*	*0.0171*	*0.3701*
Robust Mahalanobis	*0.0248*	*1.5649*	*0.0190*	*0.4698*
Logit [PS]	*0.0282*	-	*0.0190*	-

Figure S1. Covariate balancing summary

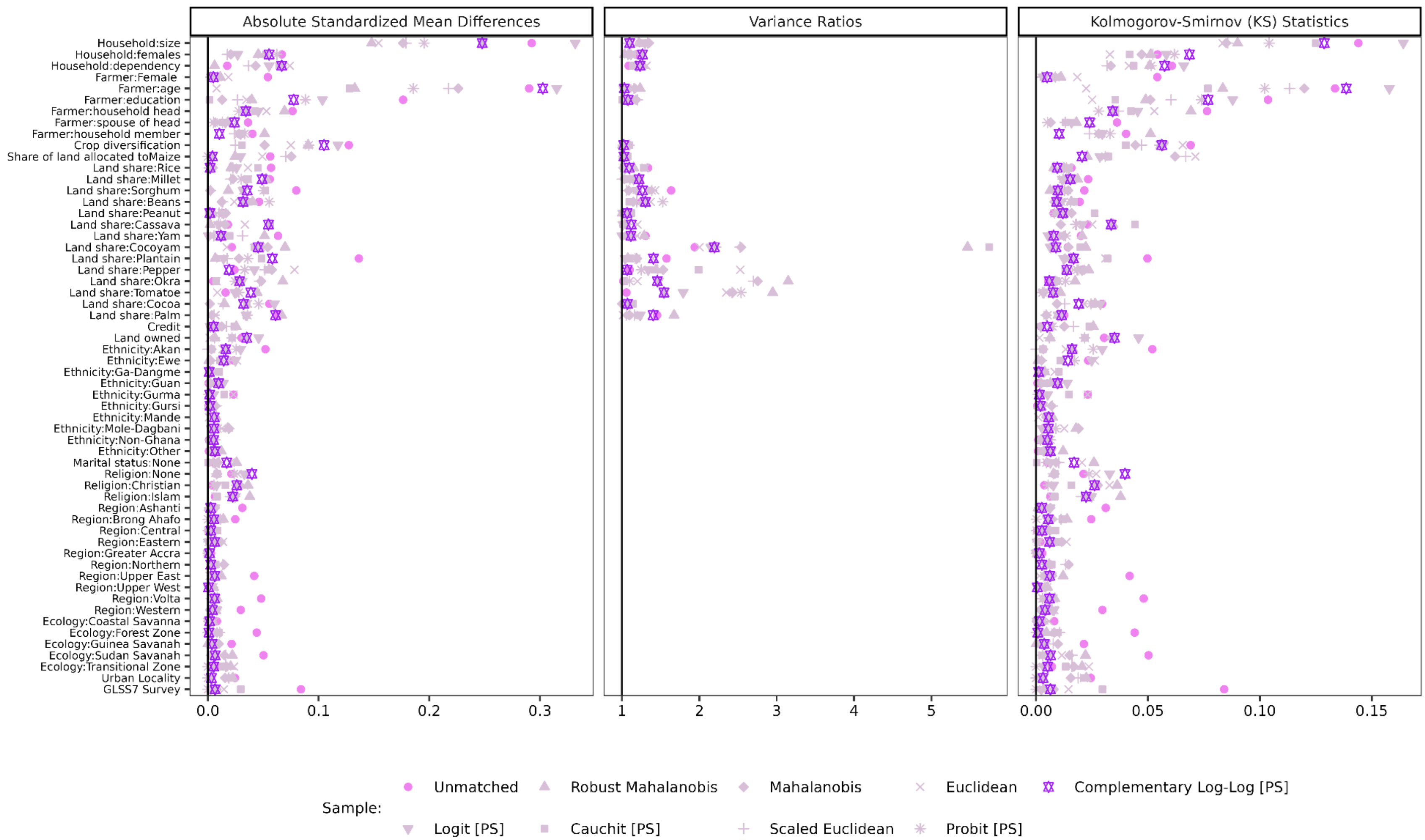
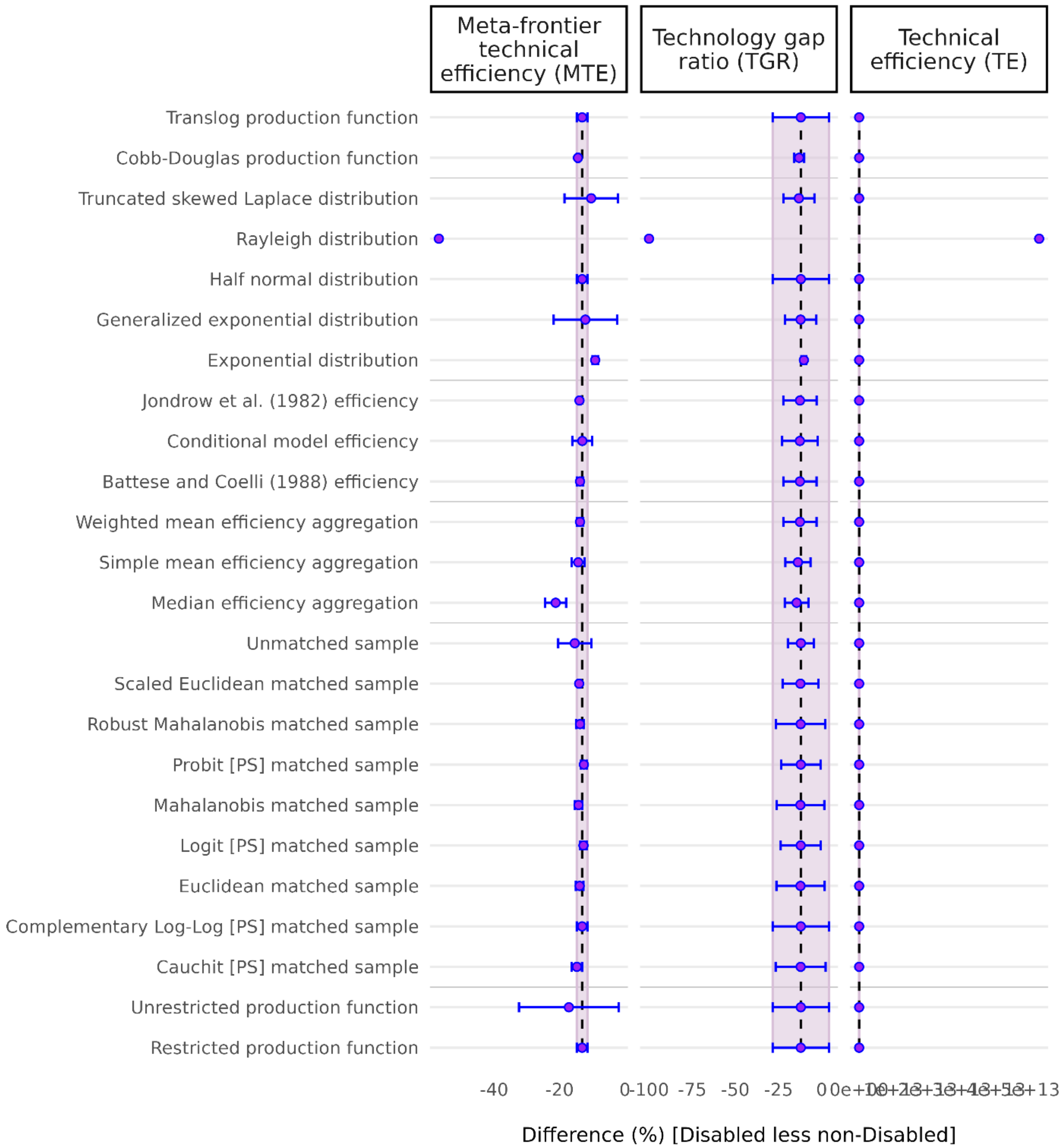


Figure S2. Alternative Model Specifications indicate a Gradual Decline in the Association between Farmer Disability and Crop Production Output in Ghana (2012–2017)



Meta Stochastic Frontier Analysis was jointly performed on Ghana Living Standards Survey [waves 6 and 7]). Standard errors were estimated via the jackknife resampling method by iteratively generating 100 resampled datasets by randomly excluding one enumeration area from each survey for every resample.